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

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Abstract

I study the impact of the recent rise in remote work on households' consumption, wealth and housing decisions, examining both short-run and long-run effects. Using detailed UK property-level housing data and a heterogeneous agent model with endogenous housing tenure and city geography, I show that remote work shifts households' housing demand by increasing the demand for space and reducing the commuting costs. It affects where people live in the city and their housing wealth accumulation. The effects vary by access to remote work, income, and wealth. The rise in work-from-home can be compared to a suburb-wide gentrification shock as wealthy telecommuters opt for larger suburban homes, displacing marginal owners who turn to renting. In the long-run, work-from-home leads to the rise of a *tele-premium*. The housing market acts as the bridge through which the effects of work-from-home spill over to workers who cannot telecommute.

Keywords: WFH, Housing Demand, City Structure, Inequality

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

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1 Introduction

The recent rise in remote work has persisted well beyond the height of the pandemic, reaching a substantial share of the workforce. In the UK, for instance, between September 2022 and January 2023, approximately 44% of workers were still working from home. This change raises important new challenges: workers may require more space at home to maintain productivity, and their commuting patterns have changed significantly, with fewer trips to the office. Moreover, not all occupations are equally suited to remote work—it is far more feasible for an economist than for a truck driver, for example. This paper addresses the following questions: How does work-from-home (WFH) reshape households' housing demand? Should workers who cannot work remotely be concerned? Will WFH affect inequality in the short and long run?

I begin by providing novel motivational evidence on the evolution of house prices and rents in the London metropolitan area. Using a hedonic pricing schedule, I show that the penalty for distance from the city center has decreased by 7.5% since February 2020 and the rise of remote work. This represents a flattening of the distance price gradient. I then develop a dynamic spatial heterogeneous-agent model with remote work. I use this framework to investigate the effects of a rise in the preference for remote work. In the model, house prices and rents are determined in equilibrium in each location of the city, allowing for general equilibrium effects of WFH-induced changes in housing demand. I find that remote work is the main driver of increased housing demand and its spatial reallocation, accounting for three-quarters of both the overall rise in house prices and the flattening of the distance gradient across the city. In the long run, the expansion of WFH leads to a *tele-premium*—an additional benefit for workers in occupations where remote work is feasible. Those who cannot work from home are crowded out of homeownership and experience welfare losses.

The development of remote work arrangements is particularly interesting because it offers greater flexibility to only a subset of the workforce. In this sense, it constitutes an asymmetric change that benefits workers who were already relatively privileged.[1] This paper argues that the housing market acts as the bridge through which the effects of WFH spill over to workers who cannot telecommute. The housing market plays an essential role in the propagation of the shock. The main contribution of this paper is to be the first to study the spread of remote work while modeling wealth and housing accumulation in general equilibrium. This allows for a direct link between the assets affected by demand and valuation changes, and the households who own them. Endogenous housing and capital accumulation in a spatial general equilibrium framework is essential to quantify the pass-through effects of remote work on non-telecommuters.

To conduct the empirical analysis, I use property-level real estate data that link house prices and rents to detailed dwelling characteristics. These data are constructed by merging three datasets and include the universe of residential property transactions in the United Kingdom since 1995, as well as all rental listings on the Zoopla website for England and Wales between 2014 and 2021. Using a hedonic pricing schedule, I show that the period since the rise in remote work has seen a flattening of the

[1] A large body of research shows that employees in low-WFH occupations tend to have lower education and earnings (Chetty et al., 2021; Althoff et al., 2022; Mongey et al., 2021).

distance gradient—that is, a decline in the penalty for living farther from the city center. Since February 2020, the distance penalty for the average house in the suburbs (beyond Zone 2 of the London Underground) relative to the average house in the city center (Zones 1 and 2) has fallen by 7.5%. For house prices, the flattening of the distance gradient occurs only for properties larger than the median size, suggesting that remote work is a key driving force behind this change.

I then explore the consequences of WFH on households through the lens of a theoretical framework. The model is a dynamic general equilibrium, heterogeneous agent model of remote work and housing tenure embedded in space. The main components are the following. **The city**: the model has two locations - the center and the suburb - that differ in amenities, commuting cost, land and housing supply elasticity. **The jobs**: some workers are employed in occupations where they can work from home. These workers choose how to 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 (i.e households decide if they want to own or rent). Two realistic features of the housing market are included. First, to buy a house households need to provide a minimum down-payment. Second, selling properties is subject to non-convex adjustment costs. **Prices**: house prices and rents are determined in equilibrium in each location. Finally, the **incomplete market** feature enables the model to generate income and wealth distributions which interact with the financial frictions on the housing market. This enables the model to study housing affordability across the city. The model is solved numerically, and the baseline is parameterized to match key features of the UK economy prior to the rise in remote work (2016–2019).

To assess the impact of remote work on housing demand and household outcomes, I simulate a permanent shift in workers' preferences for WFH. In the baseline economy, this preference is calibrated to match the share of total work done from home by workers in telecommutable occupations using data from the first wave of the UK Time Use Survey (UKTUS, 2016). I then solve for a high-WFH economy and a transition path, where the change in preferences is calibrated to align with observed WFH patterns during the transition (UKTUS, 2021). The goal is to use short-run empirical evidence to inform long-run model predictions.

Framing the rise in WFH as a shift in preferences reflects the idea that, prior to 2020, working from home was often viewed as a form of shirking. The pandemic disrupted this perception, and many workers discovered unexpected benefits—such as the comfort of working from home and spending more time with family members or pets. Modeling the rise in WFH as a change in preferences aligns with a growing literature that uses both model-based approaches (e.g., Bagga et al. 2024; Sedláček and Shi 2024) and survey evidence to document a shift in worker preferences (e.g., Chen et al. 2023; Zarate et al. 2024; Bick and Blandin 2021; Barrero, Bloom, and Davis 2021). As an illustration, LinkedIn job posting data from February 2022 show that, although remote positions made up less than 20% of all paid listings, they attracted over 50% of total job applications.[2]

[2]To be precise, I hold other margins—such as remote work technology, commuting costs, or

The first key result is that remote work is a primary driver of the rise in housing demand and its spatial reallocation. The preference-driven shift toward WFH leads to higher house prices and rents across the city, with a larger increase in the suburb. In the model, house prices rise by 2% in the center and 5% in the suburb over the two years following the change in preferences. It explains approximately three-quarters of both the observed overall price increase and the flattening of the distance gradient in the data. This pattern reflects telecommuters' greater need for space—since they spend more time working from home—and the reduction in their commuting costs. As suburban housing is more affordable, many relocate to purchase larger, cheaper homes.

The convergence of house prices to their new steady-state values differs across locations, with suburban prices overshooting more than those in the center. This stems from differences in the composition of movers. Before the shift, most non-telecommuters own homes in the suburb. As telecommuters drive up suburban housing demand with the rise of WFH, some non-telecommuters sell their homes, realize capital gains, and relocate to the center. However, because house prices in the center are significantly higher than in the suburb, these gains are typically not enough to buy a property there immediately. Instead, they rent in the center while accumulating liquid wealth, and eventually return to homeownership—conditional on favorable income shocks. This gradual process delays non-telecommuters' impact on housing demand in the center. By contrast, wealthy telecommuters moving to the suburb can buy immediately, causing a sharp and early price increase. This timing mismatch drives the initial suburban price overshoot.

On the distributional side, remote work has heterogeneous effects across occupations, giving rise to a *tele-premium*—an additional benefit accruing to workers employed in telecommutable occupations. Inequality between occupations increases across multiple dimensions—income, consumption, liquid assets, and housing wealth. While telecommuters' homeownership rises significantly with the expansion of WFH, the opposite is true for non-telecommuters, whose ownership rate falls by 14% in the long-run. The mechanism is straightforward: increased demand for suburban housing from high-income, high-wealth telecommuters drives up prices in areas that were previously more affordable (the suburb). As a result, marginal non-telecommuter homeowners are priced out and shift toward renting. This dynamic resembles a gentrification shock affecting the entire urban periphery simultaneously.

The theoretical framework allows for the computation of welfare changes induced by the rise in remote work for non-telecommuters. Since these households never had the option to work remotely, their preferences remain unchanged throughout the experiment. Overall, non-telecommuters experience a long-run welfare loss of 0.51% in consumption equivalence. The decline is more pronounced for renters, as higher rents reduce disposable resources for consumption and saving, while rising house prices make access to homeownership more difficult. Somewhat surprisingly, homeowners also experience a welfare loss of 0.26% in consumption equivalence, despite the in-

amenities—constant. I do not claim these factors remained unchanged, but rather focus on the first-order positive shift in attitudes toward remote work as a single, clean channel within the model. This allows me to isolate and assess how far this mechanism alone can go in explaining changes in housing demand.

crease in the value of their property. This reflects several factors: reduced flexibility to move, higher user costs of housing, and the interplay between household heterogeneity and market frictions. Realizing capital gains would require selling the property, but non-convex adjustment costs make this particularly burdensome—especially for low-income, low-wealth owners, who are overrepresented among non-telecommuters.

Lastly, I use the model as a laboratory to evaluate a policy that increases the supply of new housing in the city center.[3] An example would be easing the conversion of commercial real estate into residential units. This policy reduces house prices and rents across the city—by 4% in the center and 6% in the suburb—making housing more affordable. As a result, more non-telecommuters are able to relocate to the center, and they are more likely to attain homeownership. Under this office-to-apartment conversion policy, non-telecommuters would experience average welfare gains of 0.46% in consumption equivalence, with particularly large gains for renters (equivalent to 1.13% of their current consumption). In contrast, current homeowners face a modest welfare loss due to the decline in the value of their housing assets. Nevertheless, they benefit from lower user costs of housing and greater flexibility should they decide to move, as prices and rents fall throughout the city.

Related Literature. This paper contributes to the growing literature that develops theoretical frameworks to understand how WFH reshapes urban structure. Existing studies typically adopt either an urban economics approach (e.g. Delventhal and Parkhomenko 2023; Delventhal et al. 2022; Davis et al. 2023; Monte et al. 2023; Brueckner et al. 2021; Brueckner 2024; Kyriakopoulou and Picard 2023) or a financial modeling perspective (e.g., Gupta et al. 2022). Compared to this literature, the main contribution of this paper is to incorporate liquid and housing wealth accumulation into the general equilibrium framework. By modeling endogenous housing tenure and household heterogeneity, I establish a direct link between the assets subject to demand and valuation shifts and the households who own—or aspire to own—them. This is key to understanding how changes in housing demand and urban structure affect the households who inhabit them.

This paper also relates to the empirical literature on the impact of working from home (WFH) on housing. Existing studies document a WFH-induced increase in housing demand (Mondragon and Wieland 2022; Stanton and Tiwari 2021), along with a shift in demand away from major U.S. central business districts toward suburban areas—reflected in relative changes in house prices, rents, and migration patterns of households and firms (Bloom and Ramani 2022; Gupta et al. 2021; Liu and Su 2021). While these papers rely on aggregated data (e.g., ZIP code or MSA-level indexes), I use property-level data, which allow for richer controls and a detailed analysis of the role of individual housing characteristics. Moreover, existing empirical studies on the topic offer a short-run perspective by design, while stylized models typically focus on long-run outcomes. This paper bridges the gap between these two horizons by analyzing the impact of the rise in WFH in both the short and the long run.

Naturally, my work fits within the growing literature that integrates consumption–saving decisions with residential location choices (Bilal and Rossi-Hansberg, 2021), as well as dynamic spatial models of homeownership (Greaney et al., 2025; Greaney, 2025;

[3] More precisely, the policy consists of a 5% increase in housing land permits in the city center.

Giannone et al., 2023; Sun, 2024). More broadly, it relates to research on urban affordability and the geography of inequality (Parkhomenko, 2024; Favilukis and Van Nieuwerburgh, 2021; Favilukis, et al., 2022; Fogli et al., 2023; Gobillon et al., 2022), as well as to studies examining the welfare effects of housing price changes (Kaplan et al., 2020; Berger et al., 2018; Kiyotaki et al., 2011; Sinai and Souleles, 2005). This paper applies a related framework to quantify the impact of a persistent shift in the organization of work.

Finally, this paper contributes to the literature examining the distributional impact of remote work, particularly across occupations. Much of this research highlights occupational disparities in access to remote work. For instance, Dingel and Neiman (2020) construct an occupation-based Teleworkability Index, showing that not all jobs can be performed remotely. Similarly, Chetty et al. (2021), Althoff et al. (2022), and Mongey et al. (2021) document that workers in low-WFH occupations tend to have lower education and wages, and were disproportionately affected by pandemic-related job losses. De Fraja et al. (2020) make a similar case for the UK. This paper complements these studies by adding a housing dimension to the occupation-based analysis.[4] In a complementary paper, Davis et al. (2024) study the welfare implications of the rise in remote work for renters across the city and occupations. They focus on a productivity increase associated with remote work and abstract from homeownership. In contrast, I show that the housing market serves as a key transmission channel through which the effects of remote work extend to non-telecommuters. In particular, access to homeownership plays a central role in this mechanism, as rising housing demand from telecommuters leads to increased suburban prices that crowd out marginal buyers, especially among non-telecommuters.

2 Empirical Evidence

Work-from-home is interesting because it weakens the traditional link between where people live and where they work. In this section, I provide empirical evidence on the relationship between the growth of house prices and rents and the location of properties within the city, using London real estate data.

2.1 Data

The data used for this project are at the property level and provide a mapping between house prices and rents, along with detailed dwelling characteristics. These data come from three datasets. First, I use His Majesty's Land Registry Price Paid data, which record all residential property sales in the UK since 1995. From this dataset, I extract the detailed property address, sale date, and transaction price. Because this paper also examines 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 between 2014 and 2021 for England and Wales.

[4] Incorporating real estate into the study of remote work's distributional effects is essential, as housing is not only a major expenditure but also the main asset and liability for many households (Causa et al., 2020).

These two data sources provide detailed information on prices and rents at the exact property address. However, information on dwelling characteristics is limited. To address this, I merge the Land Registry and WhenFresh/Zoopla data with the Energy Performance Certificates (EPC) dataset, which contains a rich set of property characteristics—including exact address, property type, size in square meters, number of rooms, energy rating, energy efficiency, and features such as window glazing. Since September 2008, properties must have a valid EPC to be sold or let. As a result, every Land Registry transaction and every Zoopla rental listing can be matched to an EPC record. The merging procedure uses property addresses.[5]

Remote work was extremely rare prior to March 2020, but surged at the onset of the COVID-19 pandemic. This shift, however, extended well beyond the pandemic, and has proven to be highly persistent. In the UK, the Office for National Statistics (ONS) reports that 44% of the workforce worked from home at least one day per week between September 2022 and January 2023.[6] Consequently, in the empirical analysis, I treat March 2020 as the beginning of the rise in working from home (WFH). I focus on London's Travel to Work Area (TTWA), which approximates a self-contained labour market where the majority of people both live and work. TTWAs are defined through statistical analysis of commuting patterns rather than administrative boundaries.

Table 1 provides descriptive statistics from the merged housing dataset. The sample covers the period from 2016 to 2021 for rents and from January 2016 to June 2022 for house prices. There is a delay in the Land Registry's official registration of property transactions; therefore, the analysis is restricted to transactions that occurred before 30 June 2022. Table 1 reports the number of registered property transactions, the number of rental properties listed on Zoopla, and the average transaction price, weekly rent, and property size (in square meters). The number of transactions indicates that, after slowing during the peak of the pandemic in 2020, the real estate sales market rebounded and was particularly dynamic in 2021. There is also an observable increase in the average price and size of properties sold in London over the sample period. In contrast, the number of rental listings suggests a post-COVID slowdown that persisted throughout 2021. Between 2016 and 2021, both the average weekly rent and property size remained relatively stable.

2.2 Appreciation of Suburban Properties

The first two panels of Figure 1 display changes in house prices (panel a) and rents (panel b) as a function of distance from the city center, based on the raw data. Each dot represents one of London's local authorities (e.g., Camden, Hackney). The x-axis plots the change in average house prices or rents in each local authority between the year before COVID-19 and the most recent year of data[7]. The y-axis shows the logarithm of each local authority's average distance to the city center (in meters), where the city center is defined as the location of the Bank of England. A red fitted

[5]I follow the algorithm developed by Koster and Pinchbeck (2022).

[6]Similarly, Bloom et al. (2023) find that in the UK, around 20% of new job postings in 2023 allow for at least one day of working from home per week. This share was approximately 3% before the pandemic and has been rising steadily since the end of the lockdowns.

[7]July 2021 to June 2022 for house prices, and January to December 2021 for rents.

Table 1: Descriptive Statistics (London)

House prices	2016	2017	2018	2019	2020	2021	2022
# observations	120,394	113,612	107,298	103,707	94,577	138,166	53,785
price (£)	535,851	561,016	560,973	559,234	590,254	596,919	621,961
size (m^2)	84.15	85.75	87.04	87.42	89.14	89.76	88.76
Rents							
# observations	101,170	107,382	118,868	114,840	102,271	88,914	–
weekly rent (£)	422	411	419	435	437	432	–
size (m^2)	73.58	73.28	73.46	74.79	73.30	72.53	–

line is added to each plot. Both panels reveal a clear positive relationship between real estate appreciation and distance from the city center.

In the spirit of a placebo test, panels c and d plot changes in house prices and rents between 2017 and 2019 against the logarithm of distance to the city center. In these placebo specifications, we observe no positive relationship between property appreciation and distance from the 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 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.

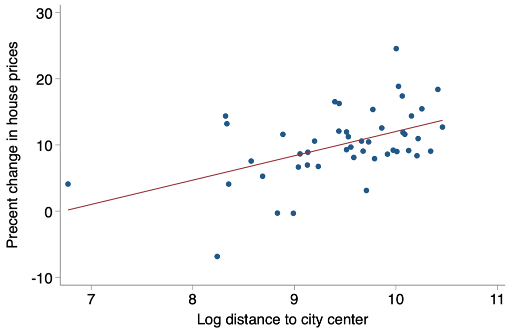
2.3 Hedonic Pricing Schedule

I now estimate the impact of proximity to the city center on house prices and rents. In addition, I examine whether the relative importance of location has changed since the rise of remote work. To this end, I employ a hedonic pricing schedule. The idea behind this approach is that a property's value reflects the combined influence of its individual characteristics, each of which contributes to its overall price. Hedonic pricing schedules allow us to estimate the marginal contribution of these characteristics. In this framework, a property's value is decomposed into the implicit prices of its components, which are obtained through regression estimates. More specifically, I estimate the model using ordinary least squares (OLS):

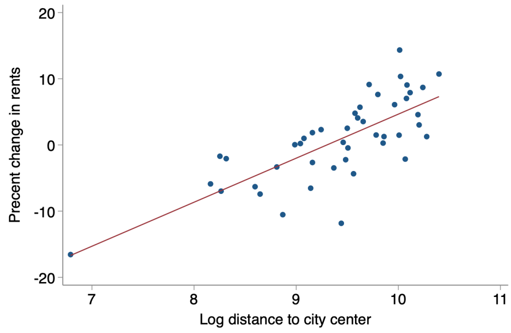
$$ln(p_{ijt}) = \delta \mathbf{1}_{\{post\}} ln(dist_i) + \gamma ln(dist_i) + \beta X_{it} + \alpha_t + \eta_j + e_{ijt} \quad (1)$$

The equation is estimated for $ln(p_{ijt})$, which denotes the transaction price or listed rent of property i in local authority j and month t. α_t represents month fixed effects, and η_j denotes local authority fixed effects. The primary variable of interest is the logarithm of the distance to the Bank of England. The indicator function $\mathbf{1}_{\{post\}}$ is equal to 1 for months after February 2020 and 0 otherwise. X_{it} is a vector of property- and neighborhood-specific controls, including the lag of the average house price in the local authority, property size, property type (Bungalow, Flat, House, or Maisonette), energy rating, energy efficiency, the presence of a fireplace, leasehold

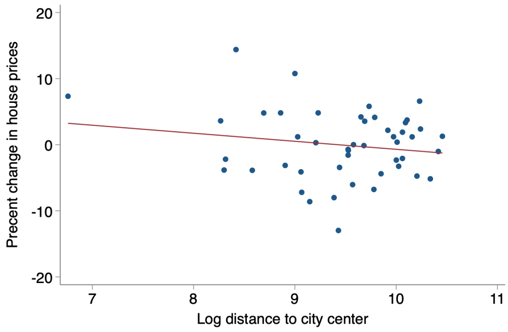
Figure 1: Growth in Property Values as a Function of Distance from the City Center



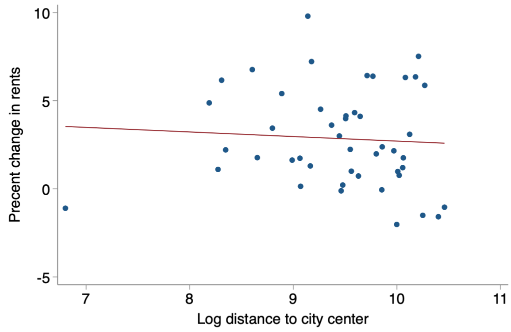
(a) House Prices



(b) Rents



(c) House Prices (Placebo)



(d) Rents (Placebo)

Notes: *Each dot represents one of London's local authorities (e.g., Camden, Hackney). In panels (a) and (b), the x-axis plots the change in average house prices and rents between the year prior to COVID-19 and the most recent year of available data (July 2021 to June 2022 for house prices, and January to December 2021 for rents). In the placebo specifications (panels (c) and (d)), the x-axis plots changes in house prices and rents between 2017 and 2019. The y-axis shows the logarithm of each local authority's average distance from the Bank of England (in meters). To reduce the influence of outliers, the top* 1% *of observations in house prices, rents, and property size (in square meters) are excluded. A linear fitted line is added to each plot.*

status, and an indicator for whether the property is newly built.[8] These controls account for neighborhood and housing quality heterogeneity.

Table 2 reports estimates of the impact of log distance to the city center on log house prices (columns 1 and 2) and log rents (columns 3 and 4). Columns 1 and 3 correspond to the main specification described above, while columns 2 and 4 present results from a placebo test. For the placebo specification, the sample is restricted to data from January 2016 to December 2019. The years 2016–2017 are treated as the pre-WFH period, and 2018–2019 as the post-WFH period. As this predates the actual onset of the pandemic, the interaction term coefficients are expected to be statistically insignificant.

[8] Available for house prices only.

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

	(1) log_price	(2) log_price	(3) log_rent	(4) log_rent
log_dist	-0.267***	-0.285***	-0.182***	-0.185***
	(0.0355)	(0.0339)	(0.0281)	(0.0264)
log_dist after WFH	0.0226**	0.0108	0.0476***	-0.0003
	(0.0071)	(0.0086)	(0.0046)	(0.0033)
Observations	723,479	440,714	620,681	433,459
Adj. R-squared	0.568	0.542	0.661	0.662
Placebo		✓		✓
Monthly FE	✓	✓	✓	✓
Local authority FE	✓	✓	✓	✓
Property controls	✓	✓	✓	✓
SE	Clust. at LA	Clust. at LA	Clust. at LA	Clust. at LA

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table reports results from OLS regressions of Equation (1), using the log of house prices (columns 1 and 2) and the log of listed rents (columns 3 and 4) as dependent variables. Property-level controls include: the lag of the average house price in the local authority, property type, energy rating, energy efficiency, presence of a fireplace, leasehold status, and an indicator for whether the property is newly built (house price regressions only). Column 1 uses data from January 2016 to June 2022. Column 3 uses data from January 2016 to December 2021, based on rent data availability. The placebo specifications in columns 2 and 4 use data from January 2016 to December 2019. To mitigate the influence of outliers, I drop the top and bottom 1% of observations in prices, rents, and property size. Standard errors are clustered at the local authority level.

The coefficients on distance are negative, consistent with the expectation that properties located farther from the city center tend to be cheaper. For instance, the coefficient on $log(dist)$ in column 1 implies that a 1% increase in distance from the city center is associated with a 0.267% decrease in house prices. This means that the average house in the suburbs (beyond zone 2 of the London Underground) faces a distance penalty of approximately 19% compared to the average house in the center (zones 1 and 2). This reflects the existence of a negative distance gradient in housing values, or a commuting penalty.

The next coefficients in Table 2 report the interaction effect between the post-February 2020 period and distance to the city center. In the non-placebo specifications (columns 1 and 3), these coefficients are positive, indicating that the penalty associated with being located farther from the city center has declined. Specifically, column 1 shows that being 1% further away from the city center reduces property prices by 0.0226% less in the post-February 2020 period compared to the pre-February 2020 period. In other words, the distance penalty associated with the average house in the suburbs relative to the average house in the city center decreased by 7.5%. This reflects a flattening of the distance gradient, or equivalently, a decline in the commuting penalty. This result is consistent with evidence from the United States, where Gupta et al. (2021) document a similar flattening of the distance gradient.

Let us now turn to the placebo specifications in columns 2 and 4. The non-interacted distance coefficients are similar to those reported in the baseline specifications, while the interaction coefficients are not statistically significant.

Table 3 explores the heterogeneity in the flattening of the distance gradient by property size. Columns 1 and 3 focus on properties with sizes below the median for house prices and rents, respectively, while columns 2 and 4 focus on properties larger than the median. For house prices, the flattening of the distance gradient occurs only for larger properties. This finding is consistent with remote work acting as a driving force behind the flattening of the distance gradient in the owner-occupier property market. This direct link will be investigated in the model presented in the next section.

Table 3: Impact of Distance to the City Center on House Prices and Rents, by Property Size

	(1) log_price	(2) log_price	(3) log_rent	(4) log_rent
log_dist	-0.241***	-0.295***	-0.164***	-0.215***
	(0.0330)	(0.0416)	(0.0279)	(0.0263)
log_dist after WFH	0.0056	0.0350***	0.0473***	0.0452***
	(0.0069)	(0.0099)	(0.0052)	(0.0035)
Observations	365,422	358,057	316,406	304,275
Adj. R-squared	0.391	0.569	0.617	0.570
Below median size	✓		✓	
Above median size		✓		✓
Monthly FE	✓	✓	✓	✓
Local authority FE	✓	✓	✓	✓
Property controls	✓	✓	✓	✓
SE	Clust. at LA	Clust. at LA	Clust. at LA	Clust. at LA

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table reports results from OLS regressions of Equation (1), using the log of house prices (columns 1 and 2) and the log of listed rents (columns 3 and 4) as dependent variables. Property-level controls include: the lag of the average house price in the local authority, property type, energy rating, energy efficiency, presence of a fireplace, leasehold status, and an indicator for whether the property is newly built (house price regressions only). Columns 1 and 3 include properties smaller than the median, while columns 2 and 4 include properties larger than the median. To mitigate the influence of outliers, I drop the top and bottom 1% of observations in prices, rents, and property size. Standard errors are clustered at the local authority level.

Finally, several robustness exercises are presented in Appendix A.1. These include adding an interaction between size and distance, using a dummy variable for the number of rooms instead of size in square meters, as well as allowing the size coefficient to vary after February 2020. The results remain similar to the baseline estimates.Appendix A.2 presents an alternative specification in which the distance coefficients are allowed to vary monthly. The results also indicate a decline in the commuting penalty.

3 The Model

3.1 Households

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

Preferences

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

$$U_{ikjt} = \frac{\left[c_{ikjt}^{\gamma} \tilde{h}_{ikjt+1}^{(1-\gamma)}\right]^{(1-\sigma)} - 1}{1-\sigma} + \eta n_{ikjt}^{H} + \overline{\epsilon_{kj}} + \sigma_{\epsilon} \epsilon_{it}(j)$$

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. η represents households' taste for working-from-home and is multiplied by the number of hours actually worked from home, n_{ikjt}^{H}. This term vanishes for households employed in non-telecommutable occupations, as for them, $n_{ikjt}^{H} = 0$. The taste parameter associated with working-from-home can be either low or high. For instance, a low parameter can be interpreted as capturing the weight of social norms associating some stigma with remote work. On the other hand, a high taste parameter can reflect workers' enjoyment of working in the comfort of their own home, or spending the day with their partner or pet. The last part of the utility function refers to the household's residential location.

Residential locations

The city is split between two locations: the center ($j = C$) and the suburb ($j = S$). All 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. Each location has amenities that are valued by all workers in a given occupation in the same way, denoted by $\overline{\epsilon_{jk}}$. 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 follow an extreme value distribution with scale parameter σ_{ϵ}. These taste shifters capture households' idiosyncratic preferences for amenities in a given location, such as proximity to friends and family, schools, and other individual considerations. Households decide in which area they want to buy or rent.

Households' labour

The labor specification is related to that of Davis, Ghent, and Gregory (2023). Each worker is endowed with one unit of time that must be allocated between hours spent working from home, n^H, and hours spent working from the office, n^O. Total time allocation satisfies:

$$1 = (1 + \chi_j)n^O_{ikjt} + n^H_{ikjt}$$

where χ_j is the commuting cost in location j. Note that commuting costs are incurred only for hours spent working at the office.

At the office, the worker produces efficient units of labor from the office, $\tilde{n}^O$, determined by:

$$\tilde{n}^O_{ikjt} = A^O_t(\nu_{it} n^O_{ikjt})^{\theta}$$

where A^O_t is a common productivity parameter for all workers at the office, ν_{it} is an idiosyncratic productivity shock that follows an autoregressive process of order one with persistence parameter ρ^{ν} and variance σ^{ν}, and θ is the share of labour in the production process.[9]

Similarly, at home, the worker produces efficient units of labor from home, $\tilde{n}^H$, determined by:

$$\tilde{n}^H_{ikjt} = A^H_{k,t}(\underline{\mathrm{h}})^{(1-\theta)}(\nu_{it} n^H_{ikjt})^{\theta}$$

where $A^H_{k,t}$ is a common productivity parameter for all workers at home. It is occupation-specific and equals zero for occupations that cannot work from home. $\underline{h}$ is the amount of space necessary for a worker to be productive at home (e.g., desk space or a home office). Having a house that is significantly larger does not increase the worker's productivity; however, it is not possible to produce any output without at least this minimum amount of space.

Workers then combine efficient units of labor produced at home and at the office into an overall efficient unit of labor, $\tilde{n}$, determined by:

$$\tilde{n}_{ikjt} = \left[(\tilde{n}^O_{ikjt})^{(\frac{\rho-1}{\rho})} + (\tilde{n}^H_{ikjt})^{(\frac{\rho-1}{\rho})}\right]^{\frac{\rho-1}{\rho}}$$

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

Finally, households are paid a wage w_t for each efficient unit of labor supplied. Labor income is given by:

$$\tilde{n}_{ikjt} w_t.$$

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 and location.

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

Renters. When they decide to rent, households pay rent q_{jt} that depends on the location j. Housing services $\tilde{h}$ that enter the renters' utility function follow:

$$\tilde{h}_{ikjt+1} = (h_{ikjt+1} - \alpha \underline{\mathrm{h}} \mathbb{1}_{WFH})$$

where α is a discount for the space that is used to work from home (if the household supplies any hours of remote work). This relates to the idea that once you have installed your work station, some space becomes unavailable for non work-related activities. Moreover, α is equal to the share of total work done from home. This follows the intuition that if a worker works remotely only half a day per week, they can set up their workstation temporarily (e.g., on the kitchen counter). However, if they work from home three days a week, they will set up a dedicated desk and proper workspace. Renters can adjust the size of their house without transaction costs.

Homeowners. For homeowners, house prices p^h_{jt} also depend on location. Housing services $\tilde{h}$ in the owners' utility function follow:

$$\tilde{h}_{ikjt+1} = \omega(h_{ikjt+1} - \alpha \underline{\mathrm{h}} \mathbb{1}_{WFH})$$

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

$$\delta p^h_{jt} h_{ikjt}$$

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

Other Assets

Households may save in one-period bonds b_{ikjt+1}. The 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_{ikjt+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):

$$m_{ikjt+1} \leq \lambda_m p^h_{jt} h_{ikjt+1}$$

where λ_m is the fraction of the house value required as collateral and h_{ikjt+1} is the size of the house bought (or $h_{ikjt} = h_{ikjt+1}$ if the household keeps their existing house).

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

$$p^h_{jt} h_{ikjt+1} - m_{ikjt+1}$$

In a scenario where house prices collapse, households with low savings and unfavorable income realizations may be unable to repay their collateralized debt. In such cases, they would sell their house and incur a large utility penalty. This substantial 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, these 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 household 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:

$$q_{jt} = \psi + p^h_{jt} - (1-\delta)\frac{1}{1+r}E\left[p^h_{jt+1}\right]$$

3.4 Final Good Producer

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

$$Y_t = N^c_t$$

where N^c_t 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:

$$\max_{I^h_{jt}} p^h_{jt} I^h_{jt} - w_t N^h_{jt}$$

$$s.t \quad I^h_{jt} = (\Theta N^h_{jt})^{\alpha_j}(\overline{L_j})^{(1-\alpha_j)}$$

where Θ is the technology parameter in the construction sector, I^h_{jt} is new housing investment in location j, N^h_{jt} 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:

$$I^h_{jt} = (\alpha_j \Theta p^h_{jt})^{\frac{\alpha_j}{1-\alpha_j}}\overline{L_j}$$

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, V^n, is presented in Appendix B.1.

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

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 $j = j'$:

$$v^h(b,h,m,\nu,k,j,j') = max\{v^{keep}(b,h,m,\nu,k,j,j'), v^{sell}(b^n,\nu,k,j,j')\}$$
$$s.t \quad b^n = b + (1-\delta)(1-F^{sell})p^h_j h - (1+r_m)m$$

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 $j \neq j'$:

$$v^h(b,h,m,\nu,k,j,j') = v^{sell}(b^n,\nu,k,j,j')$$
$$s.t \quad b^n = b + (1-\delta)(1-F^{sell})p^h_j h - (1+r_m)m$$

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

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

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

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

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

3.8 Stationary Recursive Equilibrium

In the following section, variables indexed with the superscript h refer to households who start the period owning a house, and variables indexed with the superscript n refer to households who start without owning any real estate. To further ease notation, the vector of individual states for homeowners and non-homeowners are denoted as

$$x^h := (b, h, m, \nu, k, j) \in \mathbb{X}^h, \quad \text{and} \quad x^n := (b, \nu, k, j) \in \mathbb{X}^n.$$

A stationary recursive equilibrium is a set of decision rules $\{c^h, c^n, b'^h, b'^n, h'^h, h'^n, m'^h, m'^n,$ $(n^H)^h, (n^H)^n, (n^O)^h, (n^O)^n, j'^h, j'^n, keep^h, sell^h, sellandbuy^h, sellandrent^h, buy^n, rent^n\}$, value functions $\{V^h, V^n, V^{keep}, V^{sell}, V^{rent}, V^{buy}\}$, prices $\{r, r_m, p^h_j, q_j\}$, aggregate variables (aggregate total efficient units of labour, final good sector efficient units of labour, location-specific rental units, stock of houses, construction sector efficient units of labour, and housing investment) $\{N, N^c, H^r_j, H_j, N^h_j, I^h_j\}$, and stationary distributions over the state space $\{\mu^h, \mu^n\}$ such that:

1. Given prices, households solve their optimization problem with associated value functions $\{V^h, V^n, V^{keep}, V^{sell}, V^{rent}, V^{buy}\}$ and decision rules $\{c^h, c^n, b'^h, b'^n, h'^h,$ $h'^n, m'^h, m'^n, (n^H)^h, (n^H)^n, (n^O)^h, (n^O)^n, j'^h, j'^n, keep^h, sell^h, sellandbuy^h,$ $sellandrent^h, buy^n, rent^n\}$.

2. Aggregate efficient units of labour N are determined by households' decisions of location, hours worked from home, and hours worked from the office.

3. In each location j, firms in the construction sector maximize profits with associated efficient units of labour demand and housing investment $\{N^h_j, I^h_j\}$.

4. The labour market clears at the wage $w = 1$, and efficient units of labour demand in the final good sector are determined residually as $N^c = N - \sum_{j=1}^{2} N^h_j$.

5. In each location j, the rental market clears at rent q_j, and the equilibrium quantity of rental units H^r_j is:

$$H^r_j = \int_{\mathbb{X}^h} h'^h(x^h) j'^h(x^h) sellandrent^h(x^h)\, d\mu^h + \int_{\mathbb{X}^n} h'^n(x^n) j'^n(x^n) rent^n(x^n)\, d\mu^n$$

   where the left-hand side is the total supply of rental units in location j, and the right-hand side is the total demand of rental units in location j by households who sell their house and become renters and by households who remain renters.

6. In each location j, the housing market clears at price p^h_j and the equilibrium quantity of houses satisfies:

$$\begin{aligned} I^h_j - \delta H_j + \int_{\mathbb{X}^h} h sell^h(x^h)\, d\mu^h = \delta H^r_j &+ \int_{\mathbb{X}^n} h'^n(x^n) j'^n(x^n) buy^n(x^n)\, d\mu^n \\ &+ \int_{\mathbb{X}^h} h'^h(x^h) j'^h(x^h) sellandbuy^h(x^h)\, d\mu^h \end{aligned}$$

where the left-hand side represents inflows to the housing stock on the market in location j, stemming from new construction, net of depreciation, and sales by homeowners. The right-hand side captures outflows from the market housing stock due to purchases by rental companies and households—both renters and existing homeowners relocating.

7. The final good market clears:

$$
\begin{aligned}
Y = \int_{\mathbb{X}^h} c^h(x^h)\, d\mu^h + \int_{\mathbb{X}^n} c^n(x^n)\, d\mu^n + \sum_{j=1}^{2} \left[F^{sell} p_j^h \int_{\mathbb{X}^h} hsell(x^h)\, d\mu^h \right] \\
+ \iota r \int_{\mathbb{X}^n} m'^n(x^n) buy^n(x^n)\, d\mu^n + \iota r \int_{\mathbb{X}^h} m'^h(x^h) keep^h(x^h)\, d\mu^h \\
+ \iota r \int_{\mathbb{X}^h} m'^h(x^h) sellandbuy^h(x^h)\, d\mu^h + \sum_{j=1}^{2} \left[\psi H_j^r \right] + G + NX
\end{aligned}
$$

where the first two terms on the right-hand side represent expenditures on the final consumption good. The next term captures transaction costs incurred by households selling their homes. The following three terms reflect collateralized debt intermediation costs—borne by renters who become homeowners, homeowners who retain their homes, and homeowners who sell and purchase a new home. Additionally, the expression includes the operating costs of rental agencies in each location, the government's provision of a public good G (which does not enter households' marginal utility), and net exports NX, representing the profits or losses of foreign financial agents supplying the safe asset and collateralized debt.

Finally, to fix ideas, the state variables are the household's occupation, location in the previous period, idiosyncratic productivity shock, and holdings of safe assets, real estate, and collateralized debt. The choice variables include non-durable consumption, savings in the safe asset, housing tenure, size of the house (whether owned or rented), new collateralized debt, current location, and the allocation of working hours between home and office.

4 Parameterization and Decision Rules

4.1 Parameterization

I parameterize the baseline model[10] to match key features of the UK economy prior to the increase in remote work (2016–2019). One period in the model corresponds to two years. I adopt 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 within the model using the method of simulated moments. The parameter values are summarized in Table 4, and the targeted moments are reported in Table 5, alongside their associated parameters. Details about the numerical implementation can be found in Appendix B.2.

[10] In steady state before the rise in remote work.

Table 4: Parameters

Parameter	Value	Description	Target
Households - general			
β	0.969	Discount factor	See Table 5
σ	2.00	Relative risk aversion	Standard value
γ	0.76	Weight of n.d.c. in utility	Davis, Ortalo-Magné 2011
Households - locations			
σ_ϵ	0.025	Location taste shock scaling	See Table 5
$\overline{\epsilon_{0S}}$	0.0	Amenities - non-telec. suburb	Normalisation
$\overline{\epsilon_{1S}}$	0.0	Amenities - telec. suburb	Normalisation
$\overline{\epsilon_{0c}}$	0.049	Amenities - non-telec. center	See Table 5
$\overline{\epsilon_{1c}}$	0.038	Amenities - telec. center	See Table 5
Households - housing			
ω	1.015	Utility bonus from owning	Kaplan, Mitman, Violante 2020
F^{sell}	7%	Selling cost	Kaplan, Mitman, Violante 2020
δ	1.5%	Annual depreciation rate	Kaplan, Mitman, Violante 2020
$h_{gridOwn}$	$[3.15; 4.03; 5.15]$	Grid for houses - owned	Kaplan, Mitman, Violante 2020
$h_{gridRent}$	$[1.92; 3.15; 4.03]$	Grid for houses - rented	Kaplan, Mitman, Violante 2020
Households - labour			
η	-0.269	Taste for WFH	See Table 5
θ	0.82	Labour share in eff. units of labour	Valentinyi, Herrendorf 2008
$\underline{\text{h}}$	0.48	Housing used to WFH	$10m^2$ office space
A^O	1.0	Pty. work from office	Normalisation
A^H	0.82	Pty. work from home	Gibbs, Mengel, Siemroth 2023
ρ	4.4	EOS WFH and WFO	Delventhal Parkhomenko 2023
χ_c	0.1273	Commuting cost - center	34.4 minutes one-way (TFL data)
χ_s	0.2368	Commuting cost - suburb	64 minutes one-way (TFL data)
	50%	Share of workers in tele. occ. (London)	ONS + ASHE
ρ^ν	0.889	Persistence of idio. productivity shock	ASHE
σ^ν	0.013	Variance of idio. productivity shock	ASHE
Construction sector			
Θ	0.046	Technology construction sector	See Table 5
α_c	0.147	Housing supply elast. - center	Drayton, Levell, Sturrock, 2024
α_s	0.153	Housing supply elast. - suburb	Drayton, Levell, Sturrock, 2024
$\overline{L}$	0.311	Land permits (entire city area)	Kaplan, Mitman, Violante 2020
	33%	Share land permits - center	Inner London (≈ TfL Zones 1–2)
	66%	Share land permits - suburb	Outer London (≈ TfL Zones 3–6)
Rental sector			
ψ	0.004	Rental cies. operating cost	See Table 5
Financial sector			
r	0.03	Interest rate	Annual interest rate of 3%
ι	33%	Intermediation wedge	Kaplan, Mitman, Violante 2020
λ_m	0.9	Debt collat. constraint	Greenwald 2018

Notes: All values are reported at the yearly frequency.

Table 5: Targeted Moments

Moment	Model	Data	Parameter	Source
Median net wealth over median income	4.91	4.91	β	Wealth and Assets Survey
Share of work done from home (telec. occ)	0.15	0.15	η	UK Time Use Survey
Share of renters (London)	0.49	0.49	ψ	Annual Population Survey
Equilibrium house prices in center	1.0	1.0	Θ	Normalisation
Relative house price suburb/center	0.63	0.63	$\overline{\epsilon_{1c}}$	Land Registry - EPC
Share telec./share non-telec - center	1.12	1.12	$\overline{\epsilon_{0c}}$	Annual Survey of Hours and Earnings
Share of movers (1 period)	0.25	0.25	σ_ϵ	English Housing Survey

Households - General

The relative risk aversion parameter σ is set to 2, implying an elasticity of intertemporal substitution equal to 0.5. I assume Cobb–Douglas preferences over non-durable consumption and housing services, as empirical evidence from micro data consistently supports an elasticity of substitution close to unity (Aguiar and Hurst, 2013; Davis and Ortalo-Magné, 2011; Piazzesi et al., 2007). The weight on non-housing consumption in the utility function, γ, is set to 0.76, following Davis and Ortalo-Magné (2011). The annual time-discount factor, $\beta = 0.969$, is jointly calibrated to match the ratio of median net wealth to median income.

Households - Locations

The city in the model is calibrated to match London. The city center corresponds to the boroughs defined by the ONS as Inner London,[11] which approximately aligns with Zones 1 and 2 of the London Underground network. The suburb represents the boroughs classified by the ONS as Outer London,[12] located beyond Zone 2 of the Underground. In the baseline steady state, I normalize the equilibrium house price in the center to 1 by adjusting the construction sector technology parameter Θ. Amenities in the suburb are normalized to 0, while $\overline{\epsilon_{0c}} = 0.049$ and $\overline{\epsilon_{1c}} = 0.038$ are jointly calibrated to match two targeted moments: the 0.63 ratio of price per square meter in the suburb relative to the center, and the 1.12 ratio of the share of telecommuters living in the center to the share of non-telecommuters. These two positive values reflect additional amenities available in the center compared to the suburb, consistent with the center's greater density of restaurants, bars, theaters, and other urban amenities. The scale parameter for the location-specific extreme value shocks is set to 0.025 to target the two-year household moving rate from the English Housing Survey. Finally, I calibrate location-specific commuting times using Transport for London (TfL) tube journey data from Larcom, Rauch, and Willems (2017). The supplementary material of the paper reports the average commuting time by tube and the associated standard error for the city of London in February 2014. I then recover location-specific commuting times consistent with these data.[13] Since the TfL data report the duration between tap-in and tap-out of the Underground, I add 20 minutes to each trip to account for the time required to walk from home to the nearest station and from the station to the workplace. The resulting one-way commuting times are 34.4 minutes for the center and 64 minutes for the suburb.

Households - Labour

In the utility function, the taste parameter associated with remote work, $\eta = -0.269$, is chosen to replicate the 15% share of total work done from home in 2016 among workers employed in telecommutable occupations. The parameter value is relatively

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

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

[13]I also use that 41% of Londoners live in central London (ASHE data).

low, consistent with Barrero, Bloom, and Davis (2021), who argue that, prior to COVID-19, working from home was associated with a social stigma. For efficient units of labour (both at home and from the office), the share of labour in production, $\theta = 0.82$, is fixed based on evidence from Valentinyi and Herrendorf (2008). The minimum housing space required to be productive from home is set to represent a $10\,\mathrm{m}^2$ office, which roughly corresponds to the average size of a room in central London. Productivity at the office is normalized to 1, while productivity from work done at home is set to 0.82. This value is chosen based on evidence from Gibbs, Mengel, and Siemroth (2023), who study IT professionals and estimate that their productivity fell by up to 18% when they switched to working from home during COVID-19. The elasticity of substitution between working from home and working at the office is set to 4.4, in line with the estimates of Delventhal and Parkhomenko (2023). Finally, the stochastic productivity shock is modeled as an AR(1) process in logs, calibrated using variance–covariance identifying restrictions based on data from the Annual Survey of Hours and Earnings (ASHE) between 2017 and 2019. The mean of the process is adjusted to be occupation-specific in order to match the fact that the average hourly wage of non-telecommutable workers is 80% of that of telecommutable workers (ASHE). The resulting quarterly persistence is 0.97, and the variance is 0.003. Additional details are provided in Appendix B.3.

Households - Occupations

In the model, workers can be employed in either telecommutable or non-telecommutable occupations. I use detailed UK vacancy postings data from Hansen, Lambert, Bloom, Davis, Sadun, and Taska (2023), which provide the share of job vacancies explicitly allowing remote work by 4-digit occupation code in 2019. I then rank occupations by their work-from-home intensity and construct two occupation groups such that 44% of the workforce belongs to the telecommutable category (44% is based on the Opinions and Lifestyle Survey from the ONS).

Households - Assets

Most parameters related to housing wealth are chosen following Kaplan, Mitman, and Violante (2020). The utility bonus from owning a house is set to 1.5%, the annual depreciation rate of housing is 1.5%, and the non-convex transaction cost incurred when households sell their home amounts to 7% of the property's value. I use a sparser version of the house size grids employed by the authors.[14] The risk-free interest rate is set at 3% per annum, and the collateralized borrowing intermediation wedge, τ, is set to 33%. The loan-to-value constraint parameter for collateralized debt, $\lambda = 0.9$, follows Greenwald (2018).

Construction and Rental Sectors

Housing supply elasticities are set using estimates for London from Drayton, Levell, and Sturrock (2024). The authors provide estimates at the local authority level, which I aggregate to obtain a housing supply elasticity of 0.17 in the center and 0.18 in the suburb. These values are lower than typical U.S.-based estimates. Low housing

[14] To reduce computational burden

supply elasticity is a well-documented issue in the UK, particularly in London. The operating cost of rental companies, $\phi = 0.004$, is calibrated to match the share of homeowners in London as reported in the 2019 Annual Population Survey. The total quantity of land permits available in the city follows Kaplan, Mitman, and Violante (2020). Inner London, corresponding to Zones 1 and 2 of the Underground, is allocated one-third of these permits.

4.2 Non-targeted Moments

This subsection presents how the model's stochastic steady state matches key moments that were not explicitly targeted during calibration. Table 6 reports these cross-sectional moments in both the model and the data.

First, the model can account for the geographic distribution of households, even after conditioning on occupation.[15] The share of households living in the center is 41% in both the model and the data—43% for telecommuters and 39% for non-telecommuters. The model also matches the residential patterns of households across the income distribution, as it tracks the share of households living in the center within each labour income quintile. These features are particularly important, as the model is used to study who can afford to live where within the city and the spatial reallocations prompted by the rise in working from home.

As is common in this class of models, the high degree of wealth concentration among the very rich—who tend to own expensive properties in central London—is not fully captured. As a result, the share of homeowners in the center is underestimated in the model simulations: 29% compared to 38% in the data. However, the model's share of homeowners in the suburb closely matches its empirical counterpart.

Finally, the model reproduces household wealth portfolios and labour income patterns by occupation and geography well. The mean share of total wealth held as real estate is 31% in the model, compared to 36% in the Wealth and Assets Survey. The model-implied ratio of average labour income in the suburb relative to the center is 89%, versus 88% in the data. In both the model and the data, the total labour income of non-telecommuters represents 70% of that of telecommuters.

4.3 Decision Rules

To understand the mechanisms at play in the model, it is useful to examine households' decision rules. Figure 2 plots the probability that a household chooses to live in the center as a function of liquid wealth.[16]

Panel a displays this decision rule for a household that begins the period without owning any real estate.[17] We first observe that the probability of choosing to live in the center is non-monotonic in liquid wealth. This arises because the probability

[15] I target the relative share of households living in the center across occupations, but not the levels.

[16] This is a probability due to the extreme value taste shocks associated with location-specific amenities.

[17] The other states are held fixed. This corresponds to a household with median income, employed in a telecommutable occupation.

Table 6: Non-targeted Moments

Moment	Model	Data	Source
Share of households living in center	0.41	0.41	ASHE
Share of telec. living in center	0.43	0.43	ASHE
Share of non-telec. living in center	0.39	0.39	ASHE
Share of bottom inc. quintile living in center	0.26	0.36	ASHE
Share of 2nd inc. quintile living in center	0.38	0.38	ASHE
Share of 3rd inc. quintile living in center	0.36	0.41	ASHE
Share of 4th inc. quintile living in center	0.44	0.44	ASHE
Share of top inc. quintile living in center	0.59	0.47	ASHE
Share of owners in center	0.29	0.38	APS
Share of owners in suburb	0.63	0.60	APS
Mean share of wealth as housing	0.31	0.36	W&A Survey
Labour income ratio suburb/center	0.89	0.88	ASHE
Labour income ratio non-telec./telec.	0.70	0.70	ASHE

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

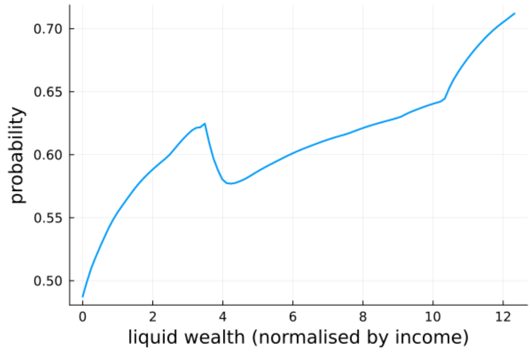
reflects a comparison of the expected value functions associated with living in the center versus the suburb, and therefore interacts with the household's other location-specific decisions. The overall upward trend in the probability of choosing the center as liquid wealth increases is expected. On average, the center is the more attractive region due to its additional amenities and lower commuting costs. These advantages are offset by higher housing prices and rents. As households become wealthier, they are more likely to afford these additional costs in order to enjoy the benefits of living in the center. Notably, the decision rule exhibits two kinks. Around a normalized liquid wealth level of 4, the probability of choosing the center drops. At this point, the household becomes able to afford homeownership in the suburb but would still be a renter in the center. At the second kink—at a normalized wealth level slightly above 10—the household can also afford to become a homeowner in the center. From this point onward, the full attractiveness of the center is restored, and the slope of the decision rule increases more sharply.

Panel b plots the same decision rule—the probability of choosing to live in the center—for two households: one that begins the period owning a house in the center (in blue), and one that begins the period owning a house in the suburb (in orange).[18] First, we observe that the probability of choosing the center is substantially higher for the household already owning a house in the center than for its suburban counterpart. This is because the suburban homeowner would need to sell their property in order to relocate, which entails adjustment costs.Moreover, the gap between the two probabilities narrows as liquid wealth increases. This reflects the fact that adjustment costs are particularly binding at lower wealth levels and become less of a

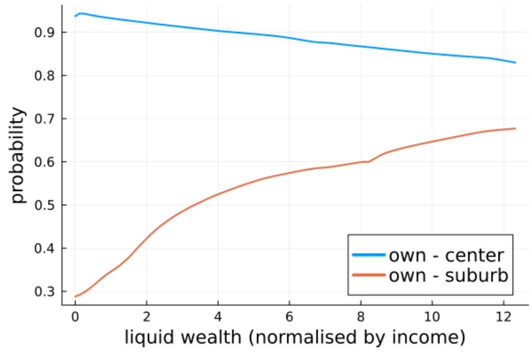
[18]The other states are held fixed. These households have median income, median housing wealth, no collateralized debt, and are employed in a telecommutable occupation.

deterrent as households accumulate more liquid assets. This pattern arises due to the non-convex nature of the adjustment costs. It highlights an interaction between the shape of adjustment costs and the distribution of wealth.

Figure 2: Decision Rules: Probability to Choose the Center



(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. Liquid wealth is expressed normalised by the average biannual income in the economy.

5 Results: the Work-from-Home Experiment

5.1 Change in Preferences

I now simulate the impact of a permanent shift in the preference parameter associated with remote work. In the baseline, the WFH preference parameter is calibrated to match the 15% share of total work done from home by workers in telecommutable occupations prior to the pandemic (2016 wave of the UK Time Use Survey, UKTUS). In the latest UKTUS wave (2021), this share rises to 55%—equivalent to slightly more than 2.5 days of remote work per week.[19] The preference parameter consistent with this level of WFH, two years after the shock, is $\eta = 0.07$. The change in the preference parameter is calibrated to be consistent with the observed evolution of WFH during the transition period. I use the short-run dynamics to discipline the model and to draw implications for the longer run.

Intuitively, workers were forced to adopt remote work during the lockdowns, and many discovered appealing aspects of it—such as working from the comfort of their own home or spending more time with a partner or pet. Modeling the rise in WFH as a change in preferences aligns with a growing literature that uses both model-based approaches (e.g., Bagga et al. 2024; Sedláček and Shi 2024) and survey evidence to document a shift in worker preferences (e.g., Chen et al. 2023; Zarate et al. 2024; Bick and Blandin 2021; Barrero, Bloom, and Davis 2021). For instance, in their Survey of Working Arrangements and Attitudes (SWAA), Barrero, Bloom, and Davis interview more than 30,000 Americans across multiple waves to investigate whether WFH will persist—and why. They find evidence of better-than-expected remote

[19]For workers in telecommutable occupations.

work experiences and a substantial decline in the stigma previously associated with WFH. For example, around 60% of respondents reported being more productive than they had expected when working from home. Prior to COVID-19, WFH was often perceived as a form of shirking; this perception shifted, with more than two-thirds of respondents acknowledging an improved view of WFH among people they know. Finally, the authors report that nearly two-thirds of SWAA respondents valued the option to work from home two to three days per week, and half considered it worth a pay increase of at least 5%.

A positive shift in attitudes toward WFH is not the only possible explanation for the recent changes in working arrangements. Another candidate is an increase in WFH productivity as workers adapted to this new mode of work and technologies like Zoom and Microsoft Teams became more widely used. I do not adopt this approach for two main reasons. First, my model takes a macroeconomic perspective on the WFH question, incorporating incomplete markets, non-convexities, and rich, multi-dimensional household choices. My focus differs from the urban economics literature on this topic. In particular, I do not explicitly model the positive agglomeration externalities associated with working in the office. As a result, modeling the rise of WFH purely as a productivity shock would likely overestimate the associated output gains, since it would ignore the countervailing effect of reduced agglomeration benefits. Second, most of the technologies required to work from home—such as internet access and videoconferencing tools—were already in place by 2019. While these technologies have seen incremental improvements, it is difficult to interpret these changes as a technological revolution, or as large enough to explain such a substantial shift in worker behavior. See Bai et al. (2021) for a discussion of the technological advances before the pandemic that already made work from home feasible. [20]

5.2 Shift in Housing Demand: the Importance of WFH

Table 7 reports changes in house prices in each city location between the two-year period preceding the rise in remote work[21] and the two-year period following it.[22] It also presents the flattening of the distance gradient, measured as the growth in the ratio of house price per square meter in the suburb relative to the center.

We first observe that, as in the data, house prices increased throughout the city but rose more sharply in the suburb. This pattern is driven by the increased demand for space among telecommuters and the reduction in their commuting costs. The model accounts for approximately three-quarters of the rise in house prices across the city and of the flattening of the distance gradient. This indicates that the shift toward remote work is the key driver of the increase in housing demand and its spatial reallocation. The remaining 25% of the rise in prices may be explained by factors not captured in the model, such as the exceptionally low interest rates during the period or the accumulation of savings by households during the pandemic. Similarly, the

[20] Another hypothesis is that the adoption of WFH results from the presence of multiple equilibria. This is the approach taken by Monte, Porcher, and Rossi-Hansberg (2023), who find that, following COVID-19, large U.S. cities transitioned to a high remote work equilibrium. The analysis of equilibrium multiplicity in environments with incomplete markets is beyond the scope of this paper.

[21] 2018–2019 in the data.

[22] 2021–2022 in the data.

Table 7: Change in House Prices and Distance Gradient

Moment	Model	Data	Share Explained by Model (%)
House price growth (%) — Center	1.86	2.37	78.44
House price growth (%) — Suburb	4.97	6.62	75.08
Flattening of distance gradient (%)	3.06	4.16	73.60

Notes: Changes in house prices are measured between the two-year period before the rise in WFH and the two-year period after. In the data, we exclude 2020 to avoid the direct effects of the pandemic, taking 2018–2019 as the pre-WFH period and 2021–2022 as the post-WFH period. The flattening of the distance gradient refers to the increase in the ratio of house price per square meter in the suburb relative to the center. *Data source:* Land Registry.

rest of the flattening of the distance gradient could be attributed to other changes, such as a relocation of certain amenities from the center to the suburbs, or evolving neighborhood preferences following the pandemic (e.g., fear of density, increased demand for green spaces, etc.).

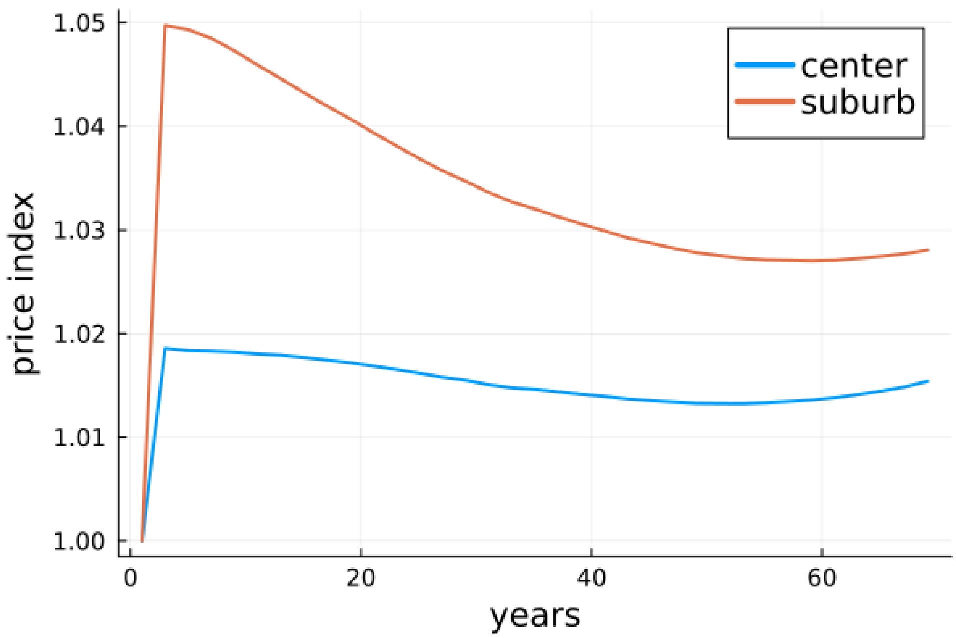
Figure 3 plots the evolution of house prices in the center (in blue) and in the suburb (in orange) following the rise in WFH over time. We observe that the convergence paths of house prices to the new steady state differ markedly across locations. House prices in the suburb overshoot significantly more than those in the center. This is driven by the composition of new movers in each location.

Most homeowners employed in non-telecommutable occupations reside in the suburb prior to the shift in working arrangements.[23] These households own the properties that appreciate most with the rise in remote work. Following the increased demand for suburban housing from wealthy telecommuters, a share of these non-telecommuters sell their homes, realize capital gains, and move to the center. However, the capital gains from selling their suburban homes are not sufficient to immediately purchase a property in the center due to the large price differential between the two locations. As a result, they become renters in the center and begin accumulating liquid wealth. Conditional on favorable income shocks, they eventually re-enter homeownership in the center. Their housing demand thus materializes gradually over time.

In contrast, the households moving to the suburb are telecommuters seeking larger properties to facilitate working from home. These households tend to be wealthy enough to purchase immediately. Consequently, the increase in demand for suburban housing is immediate, and prices rise accordingly. The difference in the speed at which housing demand materializes across locations leads to the overshooting of suburban house prices at the beginning of the transition.

[23] Suburban homeowners account for 86% of non-telecommuters with real estate.

Figure 3: House Prices



5.3 Distributional Implications

This section analyzes how the rise in remote work has affected different occupational groups, before turning to its broader implications for inequality.

Winning category – Telecommutable occupations. Following the shift in preferences associated with remote work, telecommuters re-optimize their housing tenure and neighborhood choices. The upper panel of Table 8 reports telecommuters' tenure and location before the rise in WFH and in the long run. The share of these households who own a home in the suburb increases from 37% to 64%, while the share of homeowners in the center remains stable. This implies a substantial rise in the overall homeownership rate among telecommuters. These changes in both ownership status and location reflect increased in demand for space and reduced commuting costs for this group. Moreover, the share of telecommuters renting in the suburb declines by 60%, indicating that these households are better off in the new steady state. This is the case as suburban renters represent the most disadvantaged group in the economy.

Between the two steady states, telecommuters' average labour income increases by 5%,[24] and average consumption rises by 9%. Average liquid asset holdings, however, decline by 2% as households rebalance their portfolios toward real estate. These gains span the entire population of telecommuters. For instance, Panels a and b of Figure 4 plot the distributions of consumption and housing wealth among telecommuters. In both cases, we observe a rightward shift in the distribution from the initial steady state (in blue) to the new steady state (in orange).

[24]Due to longer working hours and some degree of complementarity between working from home and working at the office.

Table 8: Location and Tenure Allocations

Share of households	Before WFH	After WFH
Telecommutable occ.		
Own - Center	18%	18%
Own - Suburb	37%	64%
Rent - Center	26%	9%
Rent - Suburb	20%	8%
Non-telecommutable occ.		
Own - Center	6%	21%
Own - Suburb	38%	17%
Rent - Center	32%	36%
Rent - Suburb	24%	26%

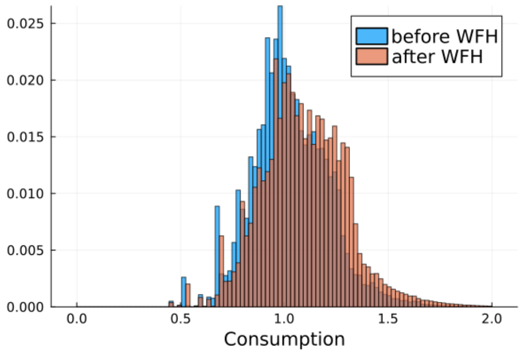
Non-telecommutable occupations. Like their telecommuting counterparts, households employed in non-telecommutable occupations adjust their location and tenure decisions between the two steady states. The lower half of Table 8 shows a reallocation of homeowners in non-telecommutable occupations from the suburb to the center. The share of non-telecommuters who own a home in the center increases from 6% to 21%, while the corresponding share in the suburb declines from 38% to 17%. Overall, the homeownership rate among non-telecommuters falls by 6 percentage points (a 14% decline) in the long run. In addition to this contraction on the extensive margin, non-telecommuters also reduce their housing consumption on the intensive margin: the average size of the homes they own decreases by 9%.

The mechanism at play is straightforward. In the suburb, properties are relatively inexpensive—recall that in the baseline steady state, the house price in the suburb is 63% of that in the center. As a result, these properties tend to be held by the least wealthy among homeowners. The rise in demand for suburban housing by telecommuting workers—who, on average, have higher wealth and income—drives up the value of formerly affordable suburban homes. Consequently, marginal homeowners are priced out of ownership and are forced into renting.

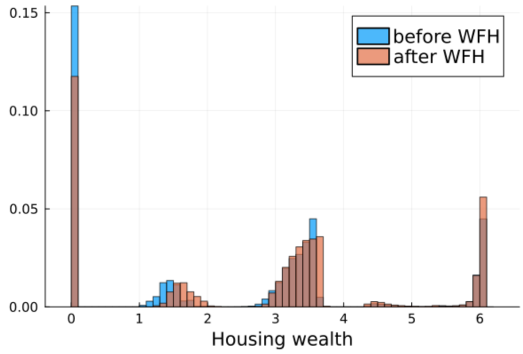
Table 9 illustrates this mechanism by displaying the location and tenure probabilities in the two steady states for the marginal non-telecommuter buyer.[25] This household begins the period without owning any real estate and has liquid wealth 45% above the population median. In the initial steady state, this marginal buyer purchases a home in the suburb with probability 0.77 and rents in the center with probability 0.23. In the new steady state, however, the same household is crowded out of the owner-occupied housing market entirely: it rents in the suburb with probability 0.75 and in the center with probability 0.25. The increased housing demand from telecommuters in the suburb, and the resulting exclusion of lower-wealth owners and buyers, resembles a gentrification shock that affects the entire urban periphery simultaneously.

[25] More precisely, the marginal buyer among non-telecommuters is defined as a household employed in a non-telecommutable occupation who purchases a house with positive probability and would not have done so with a lower level of liquid wealth or income.

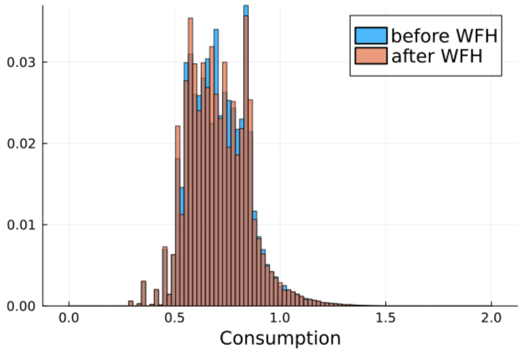
Figure 4: Distributions in the Two Steady States



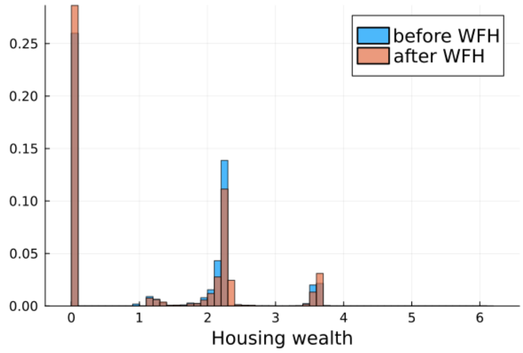
(a) Consumption (Telecommuters)



(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

Non-telecommuters' average income increases slightly, by 1%, due to lower commuting costs for those who are able to relocate to the center. However, their average housing wealth declines by 6%, and their mean consumption falls by 1%, as a result of higher house prices and rents. These changes are not limited to averages but are reflected throughout the distribution. Panels c and d of Figure 4 display a modest leftward shift in the distributions of non-telecommuters' consumption and housing wealth.

Finally, Table 10 reports the welfare losses experienced by non-telecommuters following the rise in remote work. Welfare is measured in terms of consumption equivalence variation—that is, the amount of additional consumption that households would need in the second steady state to be as well-off as they were before the shift to remote work. This measure is expressed as a percentage of second steady state consumption. Positive values indicate that households require extra consumption to be indifferent to the rise in remote work, and thus reflect a welfare loss. It is important to note that computing welfare using a utility-based measure is not straightforward for telecommuters, as this group experiences a change in a preference parameter between the two economies, rendering direct utility comparisons uninformative. This issue does not apply to workers in non-telecommutable occupations, who are unable to work remotely. Their preferences remain unchanged, so the difference in utility across steady

Table 9: Decisions of the Marginal Non-telecommuter Buyer

Steady state	P.buy - center	P.buy - suburb	P.rent - center	P.rent - suburb
Before WFH	0.0	0.77	0.23	0.0
After WFH	0.0	0.0	0.25	0.75

Notes: The marginal non-telecommuter buyer is a household who begins the period without owning any real estate and has liquid wealth 45% above the population median. *P.* stands for probability.

states provides a meaningful and consistent measure of welfare change.

Overall, non-telecommuters experience a decline in welfare. They would need to receive a consumption boost of 0.51% in the second steady state to be indifferent to the rise in remote work. The welfare loss is more pronounced for renters—amounting to 0.67% in consumption equivalence—who are already at the lower end of the consumption and welfare distributions. This loss is primarily driven by higher rents across the city, which reduce the resources available for both consumption and saving. Additionally, higher house prices make it more difficult for these housheolds to access homeownership. Somewhat surprisingly, homeowners also experience a welfare loss of 0.26% in consumption equivalence, despite the appreciation in the value of their property. This outcome is driven by a combination of factors: decreased flexibility in relocating or changing homes,[26] a higher user cost of housing,[27] and the interaction between household heterogeneity and housing market frictions. To benefit from the capital gains associated with rising house values, households would need to sell their property. However, non-convex adjustment costs make selling particularly expensive. These frictions (because the adjustment cost is non-convex) are especially discouraging for low-income and low-wealth owners, who are disproportionately represented among non-telecommuters.

Table 10: Welfare of the Non-telecommuters (Consumption Equivalence Variations)

Non-telecommuters	Consumption Equivalence Variation
All non-telecommuters	**0.51%**
Renters	0.67%
Owners	0.26%

Notes: *Notes:* Consumption equivalence variations measure the percentage increase in second steady state consumption required to keep households' utility unchanged after the rise in remote work. Positive values indicate welfare losses.

***Tele-premium* and Long-Run Inequality.** The rise in remote work has significant long-run implications for households' residential choices and tenure decisions. As a result, it also affects inequality in consumption, income, wealth, and housing—both across occupations and within the overall population. Table 11 reports the *tele-*

[26] House prices and rents increased across all areas of the city.

[27] Maintenance costs are proportional to house prices.

premium, along with several measures of inequality in consumption, income, housing, and liquid wealth, for the two steady states.

The top part of the table displays *tele-premia*, defined as the ratio of average consumption (or income, housing, or liquid wealth) of telecommuters to that of non-telecommuters. Since the rise in remote work, the *tele-premia* in consumption, income, housing, and liquid wealth have all increased substantially. For example, in the first steady state, telecommuters' average housing wealth was less than twice that of non-telecommuters; after the shift to remote work, this ratio rises to 2.64. This corresponds to a 56% increase in the housing wealth *tele-premium*. Inequality across occupations has increased along all dimensions.

The lower part of Table 11 presents several inequality measures for the overall population. Consumption and income inequality increase across all three metrics. In contrast, liquid wealth inequality slightly decreases. Interestingly, housing wealth inequality among homeowners declines in the high-WFH steady state, as reflected by a significantly lower 90th-to-median percentile ratio. This reduction in within-group housing wealth inequality can be attributed to two main factors. First, there is a valuation effect: prior to the rise in remote work, the wealthiest households tended to own properties in the Central Business District. Following the shift to WFH, the relative value of these centrally located properties declined compared to suburban homes, thereby compressing the housing wealth distribution. Second, a composition effect is at play. Lower-income, lower-liquid-wealth non-telecommuters were crowded out of homeownership and replaced by wealthier telecommuters. As a result, the homeowner group in the high-WFH economy is both wealthier and more homogeneous, contributing to the observed reduction in housing wealth inequality along the intensive margin.

5.4 Policy Experiment: Office-to-Apartment Conversions

Lastly, I use the model as a laboratory to study the implications of a policy that increases the supply of land permits in the center by 5%. A concrete example of such a policy would be facilitating the conversion of commercial real estate into residential housing. The rise in remote work has contributed to a mismatch in the real estate market: an oversupply of urban office and office-oriented retail space, and a shortage of residential properties. In the UK, the conversion of office buildings into apartments is heavily regulated. Although these regulations were recently relaxed in March 2021, they remain substantial.[28] While my current framework does not explicitly model commercial real estate, increasing the availability of land permits in the center—where commercial real estate is most concentrated—provides a reduced-form approach to analyzing the effects of loosening these conversion restrictions.

I reproduce the baseline experiment—that is, the rise in the taste for remote work—but now solve for the high WFH steady state under a scenario where the supply of land permits in the center increases by 5%. I then compare the outcomes of this policy

[28] For example, a building can only qualify for residential conversion if it has been classified as Class E (a broad category encompassing commercial, business, and service uses) for a minimum of two years. Moreover, an application for conversion can only be made if the property has remained completely vacant for at least three months.

Table 11: Consumption, Income, Housing, and Liquid Wealth Inequality

Tele-premium	Before WFH	After WFH
Consumption	1.44	1.58
Income	1.43	1.49
Housing wealth	1.69	2.64
Liquid wealth	1.24	1.29
Overall Inequality	Before WFH	After WFH
Consumption		
90th/10th ptile	2.03	2.21
90th ptile/median	1.41	1.47
Income		
90th/10th ptile	2.17	2.23
90th ptile/median	1.49	1.47
Housing wealth		
90th ptile/median	2.43	1.37
Liquid wealth		
90th/10th ptile	18.86	17.49
90th ptile/median	3.38	3.09

Notes: *Tele-premium* refers to the ratio of the average consumption (or income, housing, or liquid wealth) of telecommuters to that of non-telecommuters. The other inequality measures displayed are the 90th-to-10th percentile ratio and the 90th-to-median percentile ratio.

experiment to those of the baseline. Increasing the availability of central land permits not only reduces house prices in the center by 6% in the long run, but also lowers suburban house prices by 3%.

Table 12 presents the tenure and location allocations before the rise in remote work (Column 1), after the rise in WFH under the baseline specification (Column 2), and after the rise in WFH under the policy experiment (Column 3). Column 4 reports the changes in long-run allocations between the baseline and the policy scenario. The effects of the policy are particularly strong for non-telecommuters. Due to the large price differential between the suburb and the center, relocating to the center is especially challenging for this group. Under the policy experiment, the share of non-telecommuters living in the center is 15 percentage points higher than in the baseline. Moreover, non-telecommuters who relocate to the center are more likely to become homeowners: the share of non-telecommuters owning a house in the center is 9 percentage points higher under the policy.

Finally, lower house prices and rents reduce housing expenses, which is particularly beneficial for households at the bottom of the income and wealth distributions. Table 13 illustrates this point by reporting the welfare changes experienced by non-telecommuters after the rise in WFH in the baseline scenario (Column 1) and under the policy experiment (Column 2). As before, welfare is measured in terms of consumption equivalence variations, which represent the amount of additional consumption required for households to be indifferent to the rise in WFH. Positive values

Table 12: Location and Tenure Allocations (Policy Experiment)

Share of households	Before WFH	After WFH	After WFH (Pol.)	Change (Pol.)
Telecommutable occ.				
Own - Center	18%	18%	21%	$+3pts$
Own - Suburb	37%	64%	66%	$+2pts$
Rent - Center	26%	9%	8%	$-1pt$
Rent - Suburb	20%	8%	6%	$-2pts$
Non-telecommutable occ.				
Own - Center	6%	21%	30%	$+9pts$
Own - Suburb	38%	17%	23%	$+6pts$
Rent - Center	32%	36%	27%	$-9pts$
Rent - Suburb	24%	26%	20%	$-6pt$

Notes: Columns 1 and 2 replicate the results from Table 8. Column 3 presents the long-run tenure and location allocations under a policy experiment that increases the supply of land permits in the center by 5%. Column 4 displays the changes in long-run allocations between the baseline and the policy scenario. *Pol.* stands for policy experiment.

indicate welfare losses, while negative values reflect welfare gains. On average, non-telecommuters experience welfare gains under the policy. These gains are especially pronounced for renters—amounting to 1.13% of their current consumption—as lower rents free up resources for saving and consumption. In addition, cheaper housing makes access to homeownership easier. In contrast, homeowners experience a modest welfare loss, primarily due to the decline in the value of their housing assets. Nonetheless, they benefit from lower user costs of housing and increased flexibility should they wish to move, as both house prices and rents decline across the city.

Overall, increasing the availability of land permits in the center substantially improves the welfare of non-telecommuters compared to the baseline and emerges as a promising policy tool to mitigate some of the inequality-enhancing effects of the rise in remote work.

Table 13: Welfare of the Non-telecommuters (Policy Experiment)

Non-telecommuters	Consumption Variation	Consumption Variation (Pol.)
All non-telecommuters	**0.51%**	**-0.47%**
Renters	0.67%	-1.13%
Owners	0.26%	0.11%

Notes: The first column replicates the results from Table 10. In the second column, the consumption equivalence variations are computed between the baseline steady state and a counterfactual steady state with a 5% increase in the supply of land permits in the center. *Pol.* stands for policy experiment.

Conclusion

This paper presents novel evidence on the impact of a structural change in the way we organise labour—the adoption of working-from-home—on households' consumption, wealth, and housing decisions. It builds a new, rich theoretical framework to understand how WFH shifted households' allocation inside the city and explores the associated distributional implications. I show that WFH reshapes housing demand by increasing the taste for space and reducing workers' 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, there is the rise of a *tele-premium*, meaning some extra benefit for workers employed in occupations where remote work is feasible. What is more, WFH triggers suburb-wide gentrification: while wealthy telecommuters buy larger houses in suburban areas, it crowds out the marginal owners and pushes them into renting. I show that the housing market acts as the bridge through which the effects of WFH spill over to workers who cannot telecommute. The model developed in this paper incorporates household heterogeneity into an urban setting. An avenue for future research is to adapt this framework to answer other important remote work-related questions, such as modeling endogenous occupation choices, firms' demand for remote versus on-site work, or the endogenous response of jobs and amenities to changes in the city structure.

References

[1] M. Aguiar and E. Hurst. Deconstructing Life Cycle Expenditure. *Journal of Political Economy*, 121(3):437–492, 2013.

[2] L. Althoff, F. Eckert, S. Ganapati, and C. Walsh. The Geography of Remote Work. *Regional Science and Urban Economics*, 93, mar 2022.

[3] S. Bagga, L. F. Mann, A. Şahin, and G. L. Violante. Job amenity shocks and labor reallocation. Technical report, National Bureau of Economic Research, 2025.

[4] J. J. Bai, E. Brynjolfsson, W. Jin, S. Steffen, and C. Wan. Digital resilience: How work-from-home feasibility affects firm performance. Technical report, National Bureau of Economic Research, 2021.

[5] M. J. Barrero, N. Bloom, and S. J. Davis. Why Working from Home Will Stick. may 2021.

[6] D. Berger, V. Guerrieri, G. Lorenzoni, and J. Vavra. House prices and consumer spending. *The Review of Economic Studies*, 85(3):1502–1542, 2018.

[7] A. Bick and A. Blandin. Real-time labor market estimates during the 2020 coronavirus outbreak. *Available at SSRN 3692425*, 2021.

[8] A. Bilal and E. Rossi-Hansberg. Location as an asset. *Econometrica*, 89(5):2459–2495, 2021.

[9] J. Brueckner, M. E. Kahn, G. C. Lin, and J. K. Brueckner. A New Spatial Hedonic Equilibrium in the Emerging Work-from-Home Economy? mar 2021.

[10] J. K. Brueckner. Work-from-home and cities: An elementary spatial model. *Regional Science and Urban Economics*, page 104086, 2025.

[11] C. D. Carroll. The method of endogenous gridpoints for solving dynamic stochastic optimization problems. *Economic Letters*, 2006.

[12] O. Causa, N. Woloszko, and D. Leite. Housing, wealth accumulation and wealth distribution: Evidence and stylized facts. 2020.

[13] Y. Chen, P. Cortes, G. Kosar, J. Pan, and B. Zafar. The impact of covid-19 on workers' expectations and preferences for remote work. In *AEA Papers and Proceedings*, volume 113, pages 556–561. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203, 2023.

[14] R. Chetty, J. N. Friedman, N. Hendren, M. Stepner, and T. O. I. Team. The economic impacts of covid-19: Evidence from a new public database built using private sector data. Working Paper 27431, National Bureau of Economic Research, June 2020.

[15] M. A. Davis, A. C. Ghent, and J. M. Gregory. The Work-from-Home Technology Boon and its Consequences. feb 2023.

[16] M. A. Davis, A. C. Ghent, and J. M. Gregory. Winners and losers from the work-from-home technology boon. Technical report, National Bureau of Economic Research, 2024.

[17] M. A. Davis and F. Ortalo-Magné. Household expenditures, wages, rents. *Review of Economic Dynamics*, 14:248–261, 2011.

[18] G. De Fraja, J. Matheson, and J. C. Rockey. Zoomshock: The Geography and Local Labour Market Consequences of Working from Home. *SSRN Electronic Journal*, dec 2020.

[19] M. Delventhal and A. Parkhomenko. Spatial Implications of Telecommuting. mar 2023.

[20] M. J. Delventhal, E. Kwon, and A. Parkhomenko. JUE Insight: How do cities change when we work from home? *Journal of Urban Economics*, 127:103331, jan 2022.

[21] J. I. Dingel and B. Neiman. How many jobs can be done at home? *Journal of Public Economics*, 189, sep 2020.

[22] J. Druedahl. A Guide on Solving Non-convex Consumption-Saving Models. *Computational Economics*, 58(3):747–775, oct 2021.

[23] N. Emanuel and E. Harrington. 'working' remotely? selection, treatment, and market provision of remote work. 2021.

[24] J. Favilukis, P. Mabille, and S. Van Nieuwerburgh. Affordable Housing and City Welfare. *The Review of Economic Studies*, 90(1):293–330, jan 2023.

[25] J. Favilukis and S. Van Nieuwerburgh. Out-of-Town Home Buyers and City Welfare. *Journal of Finance*, 76(5):2577–2638, oct 2021.

[26] A. Fogli and V. Guerrieri. The end of the american dream? inequality and segregation in us cities. Technical report, National Bureau of Economic Research, 2019.

[27] E. Giannone, N. Paixão, X. Pang, and Q. Li. Unpacking moving: A quantitative spatial equilibrium model with wealth. 2023.

[28] M. Gibbs, F. Mengel, and C. Siemroth. Work from Home and Productivity: Evidence from Personnel and Analytics Data on Information Technology Professionals. *Journal of Political Economy Microeconomics*, 1(1), 2023.

[29] L. Gobillon, A. Lambert, and S. Pellet. The suburbanization of poverty: Homeownership policies and spatial inequalities in france. *Population*, 77(1):7–50, 2022.

[30] B. Greaney, A. Parkhomenko, and S. . i. e. j. Van Nieuwerburgh. Dynamic urban economics. *Available at SSRN 4897077*, 2024.

[31] B. Greany. The distributional consequences of unequal growth. 2019.

[32] D. Greenwald. The mortgage credit channel of macroeconomic transmission. 2018.

[33] S. J. Grossman and G. Laroque. Asset Pricing and Optimal Portfolio Choice in the Presence of Illiquid Durable Consumption Goods. *Econometrica*, 58(1):25, jan 1990.

[34] A. Gupta, V. Mittal, J. Peeters, and S. Van Nieuwerburgh. Flattening the curve: Pandemic-Induced revaluation of urban real estate. *Journal of Financial Economics*, 146(2):594–636, nov 2022.

[35] S. Hansen, P. J. Lambert, N. Bloom, S. J. Davis, R. Sadun, and B. Taska. Remote work across jobs, companies, and space. 2023.

[36] F. Iskhakov, T. H. Jørgensen, J. Rust, and B. Schjerning. The endogenous grid method for discrete-continuous dynamic choice models with (or without) taste shocks. *Quantitative Economics*, 8(2):317–365, jul 2017.

[37] G. Kaplan, K. Mitman, and G. L. Violante. The housing boom and bust: Model meets evidence. *Journal of Political Economy*, 128(9):3285–3345, sep 2020.

[38] N. Kiyotaki, A. Michaelides, and K. Nikolov. Winners and losers in housing markets. *Journal of Money, Credit and Banking*, 43(2-3):255–296, 2011.

[39] H. R. Koster and E. W. Pinchbeck. How Do Households Value the Future? Evidence from Property Taxes. *American Economic Journal: Economic Policy*, 14(1):207–39, feb 2022.

[40] E. Kyriakopoulou and P. M. Picard. The zoom city: Working from home and urban land structure. *Unpublished working paper*, 2022.

[41] S. Liu and Y. Su. The impact of the COVID-19 pandemic on the demand for density: Evidence from the U.S. housing market. *Economics Letters*, 207:110010, oct 2021.

[42] J. Mondragon and J. Wieland. Housing Demand and Remote Work. may 2022.

[43] S. Mongey, L. Pilossoph, and A. Weinberg. Which workers bear the burden of social distancing? *Journal of Economic Inequality*, 19(3):509–526, sep 2021.

[44] F. Monte, C. Porcher, and E. Rossi-Hansberg. Remote Work and City Structure. 2023.

[45] A. Parkhomenko. Homeownership, polarization, and inequality. *Available at SSRN 3854352*, 2024.

[46] M. Piazzesi and M. Schneider. *Inflation Illusion, Credit and Asset Pricing.* Chicago University Press, john y. campbell edition, 2008.

[47] A. Ramani and N. Bloom. The Donut Effect of Covid-19 on Cities Arjun Ramani and Nicholas Bloom NBER Working Paper. 2022.

[48] A. Saiz. The Geographic Determinants of Housing Supply. *The Quarterly Journal of Economics*, 125(3):1253–1296, 2010.

[49] P. Sedlácek and C. Shi. Macroeconomic impact of the remote work revolution. 2024.

[50] T. Sinai and N. S. Souleles. Owner-occupied housing as a hedge against rent risk. *The Quarterly Journal of Economics*, 120(2):763–789, 2005.

[51] C. T. Stanton and P. Tiwari. Housing Consumption and the Cost of Remote Work. 2021.

[52] K. Storesletten, C. I. Telmer, and A. Yaron. Cyclical dynamics in idiosyncratic labor market risk. *Journal of Political Economy*, 112(3):695–717, jun 2004.

[53] J. Sun. The distributional consequences of climate change: The role of housing wealth, expectations, and uncertainty. Technical report, Working Paper, 2024.

[54] G. Tauchen. Finite State Markov-chain Approximations to Univariate and Vector Autoregressions. *Economics Letters*, 20:177–181, 1986.

[55] Á. Valentinyi and B. Herrendorf. Measuring factor income shares at the sectoral level. *Review of Economic Dynamics*, 11:820–835, 2008.

[56] P. Zarate, M. Dolls, S. J. Davis, N. Bloom, J. M. Barrero, and C. G. Aksoy. Why does working from home vary across countries and people? Technical report, National Bureau of Economic Research, 2024.

A Additional Empirical Results

A.1 Robustness for Hedonic Price Schedule

Table 14 provides several robustness checks for the hedonic price schedules estimated in Section 2, using the log of prices as the dependent variable. Column 1 reports the baseline specification from Section 2. Column 2 adds an interaction term between size and distance to the city center. Column 3 replaces the logarithm of square meters with a dummy variable for large dwellings (defined as properties with more than three rooms) to capture property size. Finally, column 4 includes an interaction term between the post-February 2020 period and size. Table 15 reproduces these analyses using log rent as the dependent variable. The results are consistent with those of the baseline specification reported in the main text.

A.2 Alternative Hedonic Specification: Monthly Coefficients

Equation (1) in the main text evaluates the total change in the importance of distance in determining house prices and rents over the entire post-pandemic period. Another interesting exercise is to examine the distance gradients for each month within our sample.

$$ln(p_{ijt}) = \delta_t ln(dist_i) + \beta X_{it} + \alpha_t + \eta_j + e_{ijt} \tag{2}$$

Equation (2) allows the coefficients on log distance to vary by month. These coefficients capture the effect of distance on the outcome variable in each month relative to the baseline period of February 2020.

Figure 5 plots the monthly coefficients on distance from Equation (2). The 95% confidence intervals are shown in green, and the last period before COVID-19 (February 2020) is highlighted by the vertical red dotted line. This exercise serves as a test for

Table 14: Impact of Distance to City Center on House Prices

	(1) log_price	(2) log_price	(3) log_price	(4) log_price
log_dist	-0.267***	-0.187*	-0.262***	-0.266***
	(0.0355)	(0.0844)	(0.0503)	(0.0355)
log_dist after WFH	0.0226**	0.0232**	0.0278***	0.0190*
	(0.0071)	(0.0074)	(0.0055)	(0.0074)
Observations	723,479	723,479	577,226	723,479
Adj. R-squared	0.568	0.568	0.472	0.568
Monthly FE	✓	✓	✓	✓
Local authority FE	✓	✓	✓	✓
Property controls	✓	✓	✓	✓
SE	Clust. at LA	Clust. at LA	Clust. at LA	Clust. at LA

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table reports results from OLS regressions of Equation (1), using the log of house prices as the dependent variable. Property-level controls include the lag of the average house price in the local authority, property type, energy rating, energy efficiency, presence of a fireplace, leasehold status, and an indicator for whether the property is newly built. To reduce the influence of outliers, the top and bottom 1% of observations in prices and property size are excluded. Standard errors are clustered at the local authority level.

Table 15: Impact of Distance to City Center on Rents

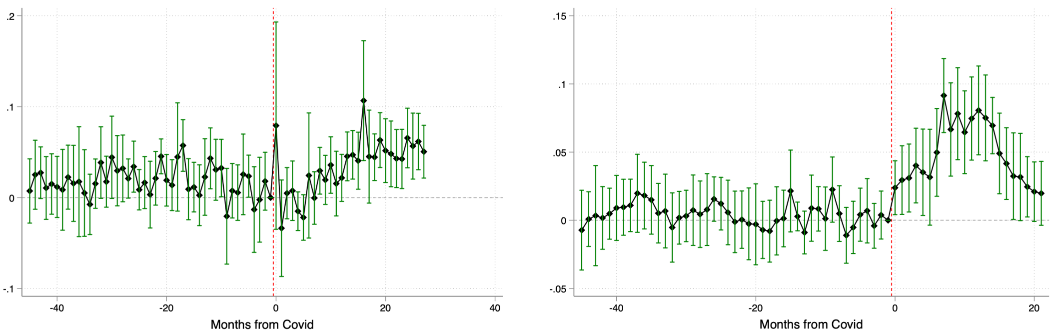
	(1) log_rent	(2) log_rent	(3) log_rent	(4) log_rent
log_dist	-0.182***	0.0914	-0.186***	-0.182***
	(0.0281)	(0.1070)	(0.0353)	(0.0281)
log_dist after WFH	0.0476***	0.0472***	0.0478***	0.0464***
	(0.0046)	(0.0043)	(0.0059)	(0.0044)
Observations	620,681	620,681	605,168	620,681
Adj. R-squared	0.661	0.662	0.533	0.661
Monthly FE	✓	✓	✓	✓
Local authority FE	✓	✓	✓	✓
Property controls	✓	✓	✓	✓
SE	Clust. at LA	Clust. at LA	Clust. at LA	Clust. at LA

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

This table reports results from OLS regressions of Equation (1), using the log of rent as the dependent variable. Property-level controls include the lag of the average house price in the local authority, property type, energy rating, energy efficiency, presence of a fireplace, and leasehold status. To mitigate the influence of outliers, the top and bottom 1% of observations in rents and property size are excluded. Standard errors are clustered at the local authority level.

Figure 5: Month-Specific Distance Coefficients (London)



(a) Distance Coefficients on House Prices

(b) Distance Coefficients on Rents

Notes: Standard errors are clustered at the local authority level. To reduce the influence of outliers, the top 1% of observations in house prices, rents, and size (in square meters) are excluded. 95% confidence intervals are shown in green

the absence of a pre-trend in the importance of distance in shaping households' housing demand. Reassuringly, no clear trend is observed before the pandemic, as most pre-February 2020 effects are not statistically significant. However, the coefficients δ_t are positive and significant in the later part of the sample, confirming the earlier finding that the penalty associated with distance from the city center decreased.

B Model Details, Numerical Implementation, and Calibration

B.1 Recursive Formulation of the Problem: Household Without Initial Homeownership

V^n denotes 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 $v^n(b, \nu, k, j, j')$, with $j' \in \{C, S\}$, 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 follow an extreme value distribution with scale parameter σ_ϵ.

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

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.

$$
\begin{aligned}
v^{rent}(b,\nu,k,j,j') = & \max_{c,h',n^O,b'} u(c,\tilde{h}') + \beta E_\nu E_\epsilon \left[V^n(b',\nu',k,j',\epsilon')\right] \\
& s.t \quad c + q_{j'}h' + b' + \leq (1+r)b + w\tilde{n} \\
& \tilde{n} = \left[\tilde{n}^{O(\frac{\rho-1}{\rho})} + \tilde{n}^{H(\frac{\rho-1}{\rho})}\right]^{\frac{\rho-1}{(\rho)}} \\
& \tilde{n}^O = A^O(\nu n^O)^\theta \\
& \tilde{n}^H = A^H(\underline{\mathrm{h}})^{(1-\theta)}(\nu n^H)^\theta \\
& 1 = (1+\chi_{j'})n^O + n^H \\
& n^H = 0 \quad if \quad k = 0 \\
& \tilde{h}' = h' - \alpha\underline{\mathrm{h}}\mathbb{1}_{n^H>0} \\
& b' \geq 0 \\
& \nu' \sim \Upsilon(\nu)
\end{aligned}
$$

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

$$
\begin{aligned}
v^{buy}(b,\nu,k,j,j') = & \max_{c,h',n^O,b',m'} u(c,\tilde{h}') + \beta E_\nu E_\epsilon \left[V^h(b',h',m',\nu',k,j',\epsilon')\right] \\
& s.t \quad c + p^h_{j'}h' + b' \leq (1+r)b + w\tilde{n} + m' \\
& \tilde{n} = \left[\tilde{n}^{O(\frac{\rho-1}{\rho})} + \tilde{n}^{H(\frac{\rho-1}{\rho})}\right]^{\frac{\rho-1}{(\rho)}} \\
& \tilde{n}^O = A^O(\nu n^O)^\theta \\
& \tilde{n}^H = A^H(\underline{\mathrm{h}})^\theta(\nu n^H)^{(1-\theta)} \\
& 1 = (1+\chi_{j'})n^O + n^H \\
& n^H = 0 \quad if \quad k = 0 \\
& \tilde{h}' = \omega(h' - \alpha\underline{\mathrm{h}}\mathbb{1}_{n^H>0}) \\
& b' \geq 0 \\
& m' \leq \lambda_m p^h_{j'}h' \\
& \nu' \sim \Upsilon(\nu)
\end{aligned}
$$

B.2 Numerical Implementation

I solve for the model's policy functions by combining the DC-EGM with taste shocks of Iskhakov et al. (2017) and the NEGM+ algorithm developed by Druedahl (2021). These methods extend the endogenous grid point method of Carroll (2006) to settings with non-convexities and exploit the nested structure of the household problem. An additional layer of optimization is achieved using an enhanced interpolation method. I solve for household policies on 400-point grids for cash-on-hand and liquid assets, an 5-point grid for collateralized debt, and a 3-point grid for house sizes. The autoregressive process for idiosyncratic productivity shocks is discretized into a seven-state Markov chain using the method proposed by Tauchen (1986). The value function is iterated until convergence, using the absolute value of the largest difference as the error metric, with a tolerance level of 10^{-4}. The model is solved in general equilibrium by finding the two equilibrium house prices—one for the center and one for the suburb—using the Broyden algorithm. Finally, non-liner transition dynamics are computed using perfect foresight, solving for the equilibrium sequence of prices over the entire transition period.

B.3 Calibration of the Stochastic Productivity Process

The idiosyncratic productivity process is calibrated using data from the Annual Survey of Hours and Earnings (ASHE) between 2017 and 2019. In period t, the logarithm of worker i's hourly wage, $\log(y_{it})$, is given by:

$$
\begin{aligned}
log(y_{it}) &= Z'_{it}\beta + \tilde{y_{it}} \\
\tilde{y_{it}} &= P_{it} + \epsilon_{it} \\
P_{it} &= \tilde{\rho} P_{it-1} + u_{it} \\
\epsilon_{it} \sim i.i.d, &\quad u_{it} \sim \mathcal{N}(0,\, \sigma_u^2)
\end{aligned}
$$

where Z_{it} is a set of observable characteristics of worker i. The hourly wage residual, $\tilde{y}_{it}$, consists of a persistent component, P_{it}, which follows an autoregressive process of order one (AR(1)), and an i.i.d. measurement error term, ϵ_{it}, which is discarded. Hourly wage residuals are obtained by performing a standard OLS regression of the logarithm of workers' hourly wage on gender, age, age squared, occupation, industry, region, and dummy variables for year, full-time employment, job tenure longer than one year, and firm type (private, public, or non-profit). I then use the following variance–covariance identifying restrictions to recover the AR(1) parameters of the persistent component:

$$
\begin{aligned}
\frac{Cov(\tilde{y_{it}}, \tilde{y_{it-2}})}{Cov(\tilde{y_{it}}, \tilde{y_{it-1}})} &= \tilde{\rho} \\
Cov(\tilde{y_{it}}, \tilde{y_{it-1}}) &= \tilde{\rho} * \sigma_P^2 \\
(1 - \tilde{rho}^2) * \sigma_P^2 &= \sigma_u^2
\end{aligned}
$$

I then discretize the process into a seven-state Markov chain using the Tauschen method. Finally, the grid is adjusted so that the average productivity of workers in non-telecommutable occupations is 80% of that of workers in telecommutable occupations. This matches the empirical fact that, in 2019, the average hourly wage of workers in non-telecommutable occupations was 80% of that of workers in telecommutable occupations.

C Additional Results

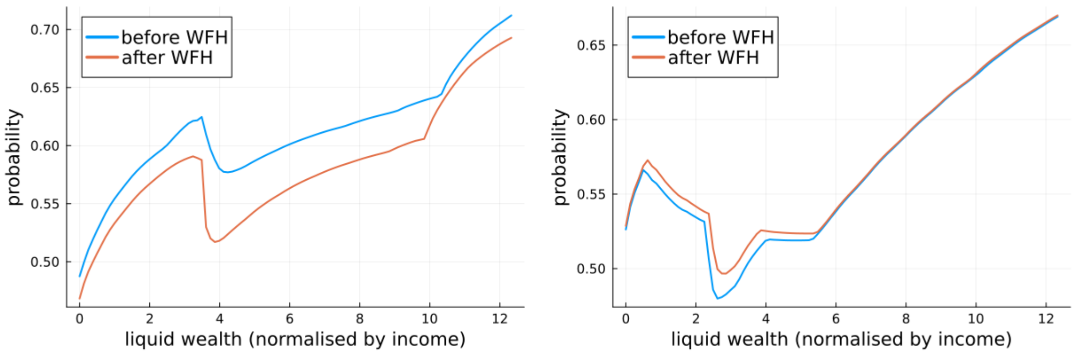
C.1 Decision Rules and WFH Experiment

Figure 6 plots households' probability to choose to live in the center over the distribution of liquid wealth in the first steady state (in blue), and in the second steady state (in orange). Panel a displays this decision rule for a household employed in a telecommutable occupation who starts the period without owning any real estate.[29]

[29]More precisely, it is a household with median income.

Panel b displays this decision rule for a household employed in a non-telecommutable occupation who starts the period without owning any real estate.[29] This exercise provides a sanity check. For the household who can WFH, the probability to move to the center is lower in the high WFH steady state, the opposite is true for the household who cannot telecommute.

Figure 6: Decision Rules: Probability to Choose the Center



(a) Telecommutable Occupation (b) Non-telecommutable Occupation

Notes: Median income households without any real estate wealth at the start of the period.