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

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March 10, 2026

Abstract

This paper studies the impact of the recent rise in remote work on households' consumption, wealth and housing decisions, examining both short-run and long-run effects. I develop a general equilibrium dynamic spatial heterogeneous-agent model featuring remote work and homeownership, and validate the main mechanism with detailed property-level housing data for London. 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

*Sciences Po. Email: morgane.richard@sciencespo.fr. I am indebted to Morten Ravn, Ralph Luetticke, and Franck Portier for the guidance and support throughout this project. I am grateful to Stephen Hansen for generously sharing the WFH data from his project "Remote Work across Jobs, Companies, and Space" with Lambert, Bloom, Davis, Sadun, and Taska (2023). Finally, I would like to thank Adrien Auclert, Adrien Bilal, Nick Bloom, Richard Blundell, Elena Casanovas Navarro, Axelle Ferriere, Laurent Gobillon, Brian Greaney, Christian Hellwig, Juan Herreño, Markus Karlman, Thomas Lazarowicz, Albert Marcet, Justinas Markauskas, Kurt Mitman, Enrico Miglino, Ryungha Oh, Andrii Parkhomenko, Monika Piazzesi, Lukasz Rachel, Jose-Victor Rios-Rull, Cezar Santos, Martin Schneider, Vincent Sterk, and seminar participants at UCL and various institutions for suggestions that have substantially improved this paper. I gratefully acknowledge financial support from the Stanford Institute for Economic Policy Research, the ESRC Centre for Macroeconomics and the UCL NSA fellowship. The rental data for this research have been provided by the Consumer Data Research Centre, an ESRC Data Investment.

1 Introduction

In recent years, the widespread adoption of remote work has fundamentally transformed how and where people work. In the UK, for instance, between September 2022 and January 2023, approximately 44% of workers were working from home at least part of the time. This shift raises important new challenges: workers may require more space at home to maintain productivity, and commuting patterns have changed significantly, with fewer trips to the office. Moreover, not all workers are equally able to remote work — it is far more feasible for an economist than for a truck driver. How does working from home reshape households' housing demand? Should workers who cannot work remotely be concerned about its consequences? Will WFH affect inequality in the short and long run?

This paper addresses these questions by developing a general equilibrium dynamic spatial heterogeneous-agent model featuring remote work and homeownership, and by validating the main mechanism with detailed real estate data for London. On the theory side, I need three key modeling features to study the changes in housing demand induced by remote work and their distributional implications. The first key element is homeownership itself. Households decide whether to own or rent their home, and purchasing a home requires accumulated wealth as a minimum downpayment is needed. The second key element is the spatial dimension. Remote work loosens the link between where people live and where they work, potentially shifting housing demand across locations within the city. Finally, incomplete markets allow the model to speak to housing affordability across the city and how it evolved with remote work. I find that the housing market acts as the channel through which the effects of remote work spill over to workers who cannot telecommute. WFH raises housing demand among telecommutable workers throughout the city, but particularly in the suburbs - where the most affordable properties were located - so that general equilibrium forces erode housing affordability citywide. In the long run, the expansion of WFH gives rise to a *tele-premium*: an additional benefit accruing to workers in occupations amenable to remote work. Those who cannot work from home are crowded out of homeownership and experience welfare losses. I then bring the model's central prediction to the data. The relative appreciation of suburban properties is the key force underlying the theoretical results, making its empirical validation particularly important. Using detailed real estate data for London, I find that, since the rise of remote work, the penalty for distance from the city center has fallen by 7.7%. Remote work alone can account for half of this decline.

Without modeling homeownership and general equilibrium, WFH does not impact non-telecommuters. The main contribution of this paper is to highlight the role of the housing market as the bridge channeling the effects of remote work from workers who can partake in it to those who cannot. This paper is the first to study the spread of remote work while jointly modeling homeownership and wealth accumulation in general equilibrium, establishing a direct link between the assets affected by valuation changes and the households who own them. The spillover to non-telecommuters is particularly important in the context of WFH, as the flexibility it offers accrues only to the subset of the workforce that was already relatively privileged.[1]

[1] A large body of research shows that workers in low-WFH occupations tend to have lower levels of

To go into further detail, the model is a dynamic general equilibrium heterogeneous-agent model of remote work and housing tenure embedded in space. Its main components are as follows. **The city**: the model features two locations — the center and the suburb — that differ in amenities, commuting costs, land, and housing supply elasticity.[2] **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 allows the model to speak to who can afford to live where within the city.

The model's 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 then 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 discipline the model and inform long-run predictions.

Framing the rise in WFH as a shift in preferences reflects the idea that, prior to 2020, working from home was often perceived 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 the ability to spend more time with family or pets. Modeling the rise in WFH as a preference change aligns with a growing literature that draws on both structural approaches (e.g., Bagga et al. (2025); Sedlácek and Shi (2024)) and survey evidence to document a positive shift in workers' attitudes toward remote work (e.g., Barrero et al. (2021); Chen et al. (2023); Zarate et al. (2024); Bick et al. (2023)).[3] As an illustration, LinkedIn job posting data from February 2022

education and earnings Chetty et al. (2020), Althoff et al. (2022), Mongey et al. (2021), Adams-Prassl et al. (2022).

[2] I assume that households move within the city but abstract from migration beyond its boundaries. Two considerations justify this. First, I focus on the persistent form of WFH that has prevailed since the end of the pandemic — namely, hybrid remote work. If workers are required to be in the office two days a week, for instance, relocating to another city altogether is unlikely to be optimal. Second, this simplification would be problematic if the city I study — London — had experienced exceptional in- or out-migration since the rise of remote work. Appendix E plots the population of the Greater London Metropolitan Area between 2004 and 2025 and shows no discernible change in trend since the rise of remote work.

[3] To be precise, I hold other margins constant — such as remote work technology, commuting costs, and amenities. 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.

show that, although remote positions accounted for less than 20% of all paid listings, they attracted over 50% of total applications.

The first key result is that, in the long-run, remote work reshapes housing demand and its allocation within the city. This is driven by workers in telecommutable occupations, who respond to the WFH preference shift in two ways. First, they require more space for a home office, raising housing demand throughout the city. Second, they commute less frequently, making suburban living more attractive. Since suburban housing is cheaper, remote workers relocate to purchase larger, more affordable properties outside the center. As a result, housing demand rises more in the suburb than in the center, driving a relative appreciation of suburban prices. In the long run, house prices and rents rise everywhere, but more so in the suburb.

Along the transition path, however, price dynamics differ across locations, reflecting who the new movers in each neighborhood are in the wake of the shock. Telecommuters seeking larger properties tend to be sufficiently wealthy to purchase without delay, so suburban demand rises immediately and prices adjust accordingly. In the center, by contrast, prices initially dip. The new movers there are non-telecommuters who sold their suburban homes to relocate, but since the price gap between locations is large, the capital gains from selling are typically insufficient to purchase in the center. As a result, these households transition into renting, dampening center demand in the short run.

The relative appreciation of suburban prices has significant distributional consequences. While homeownership rises substantially among telecommuters, the opposite holds for non-telecommuters, whose ownership rate falls by two-thirds 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). Marginal non-telecommuter homeowners are priced out and shift toward renting — a dynamic that resembles a gentrification shock hitting the entire urban periphery simultaneously. More broadly, remote work generates heterogeneous effects across occupations, giving rise to a *tele-premium*: an additional benefit accruing to workers in telecommutable occupations. Inequality between occupations widens across multiple dimensions — income, consumption, and housing wealth.

The model allows for the computation of welfare changes induced by the rise in remote work for non-telecommuters.[4] In the long run, non-telecommuters experience an average welfare loss of 0.47% in consumption equivalence. The decline is more pronounced for renters, for whom higher house prices and rents directly erode disposable income and make homeownership increasingly out of reach. Surprisingly, homeowners also experience a welfare loss of 0.18% in consumption equivalence, despite the increase 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.

[4] Since these households never had the option to work remotely, their preferences remain unchanged throughout the experiment.

Including the transition period dampens these welfare losses: house prices and rents rise only gradually, and non-telecommuters who owned property prior to the shock — predominantly in the suburb, precisely the location that appreciated most — experienced short-run gains from the rise in their housing wealth.

I then use the model as a laboratory to evaluate a policy that expands the supply of new housing in the city center — for instance, through the conversion of commercial real estate into residential units.[5] Expanding central housing supply not only reduces house prices in the center by 1% in the long run, but also dampens the rise in suburban prices to just 0.5%. As a result, more non-telecommuters are able to retain homeownership, and their average welfare loss turns into a gain of 0.09% in consumption equivalence.

Most theoretical results rest on a single mechanism: the relative appreciation of suburban properties. Given the importance of this driving force, I test this prediction in the data using property-level real estate data that link house prices to detailed dwelling characteristics for the city of London. These data are constructed by merging two datasets that cover the universe of residential property transactions in the United Kingdom since 1995. Exploiting the richness of these dwelling-level characteristics, I estimate a hedonic pricing schedule and show that the period since the rise of remote work has been marked by a flattening of the 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 suburban property (beyond Zone 2 of the London Underground) relative to the average central property (Zones 1 and 2) has fallen by 7.7%. This empirical finding validates the model's central mechanism. I then exploit the model-implied decline in the distance penalty to assess the contribution of remote work alone to the spatial reallocation of housing demand. Comparing the model-implied change in the distance gradient to its empirical counterpart, I find that the rise in WFH accounts for approximately half of the observed reallocation of housing demand.

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), Monte et al. (2023), Davis et al. (2023), Brueckner et al. (2021), Brueckner (2025), Duranton and Handbury (2023), Behrens et al. (2024), Kyriakopoulou and Picard (2022)) 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.[6]

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

[6] Gamber et al. (2023) set up a dynamic model of homeownership to study the impact of exogenous stay-at-home shocks on house prices during the pandemic. Their focus is on time spent at home, and they abstract from location choice as well as from explicitly modeling remote work.

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 (Ramani and Bloom (2022), Gupta et al. (2022), 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 using the short run to discipline the model and inform long-run predictions. This connects to Howard et al. (2023), who examine post-pandemic housing demand dynamics in the short and long run, with a focus on short- and long-run housing supply elasticity.

Naturally, my work fits within the growing literature that integrates consumption and saving decisions with residential location choices (Bilal and Rossi-Hansberg (2021)), as well as dynamic spatial models of homeownership (Greaney et al. (2024), Greaney (2023), Giannone et al. (2023), Sun (2024)). More broadly, it relates to research on urban affordability and the geography of inequality (Parkhomenko (2025), Favilukis and Van Nieuwerburgh (2021), Favilukis et al. (2023), Fogli and Guerrieri (2019), 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. (2020), Althoff et al. (2022), Mongey et al. (2021), and Adams-Prassl et al. (2022) 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. 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)). 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.

2 The Model

2.1 Households

The economy is populated by a continuum of infinitely-lived households of measure 1, indexed by $i \in (0,1)$, living in a metropolitan area consisting of a center 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. Moving across locations entails a moving cost F^{move}.

Households' labour

The labor specification is related to that of Davis et al. (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.[7]

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

Households have the option to rent or own their house. Houses are characterized by their size and location.

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:

$$\tilde{h}_{ikjt+1} = h_{ikjt+1} - n^H \underline{\mathrm{h}}$$

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

where the second term reflects a discount for the space that is used to work from home. This relates to the idea that once you have installed your work station, some space becomes unavailable for non work-related activities. The discount in housing services is proportional 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 a proper workspace, thereby crowding out a greater share of their living space. Finally, 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:

$$\tilde{h}_{ikjt+1} = \omega h_{ikjt+1} - n^H \underline{\mathrm{h}}$$

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.

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. I also assume that when households retain their existing home, they keep their outstanding balance of collateralized debt (abstracting from refinancing).

2.2 Financial Sector

The supply side of the economy is close to that of Kaplan et al. (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.

2.3 Final Good Producer

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

$$Y_t = N_t^c$$

where N_t^c is the quantity of efficient units of labour employed in the final good production sector. The competitive wage is given by: $w_t = 1$.

2.4 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:

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

2.5 Construction Sector in Location j

The construction sector in area j solves:

$$\max_{I_{jt}^h} p_{jt}^h I_{jt}^h - w_t N_{jt}^h$$

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

where Θ is the technology parameter in the construction sector, I_{jt}^h is new housing investment in location j, N_{jt}^h 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:

$$I_{jt}^h = (\alpha_j \Theta p_{jt}^h)^{\frac{\alpha_j}{1-\alpha_j}}\overline{L_j}$$

2.6 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.

2.7 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 A.1. The stationary equilibrium definition can be found in Appendix A.2.

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

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.

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

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 Parameterization and Decision Rules

3.1 Parameterization

I parameterize the baseline steady state of the model 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 1, and the targeted moments are reported in Table 2, alongside their associated parameters. Details about the numerical implementation can be found in Appendix A.3.

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 and Schneider (2008)). 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,[8] 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,[9] 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 $\overline{\epsilon_{0c}} = 0.044$ and $\overline{\epsilon_{1c}} = 0.039$ 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

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

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

Table 1: Parameters

Parameter	Value	Description	Target
Households - general			
β	0.969	Discount factor	See Table 2
σ	2.00	Relative risk aversion	Standard value
γ	0.76	Weight of n.d.c. in utility	Davis and Ortalo-Magné (2011)
Households - locations			
σ_ϵ	0.036	Location taste shock scaling	See Table 2
F^{move}	0.011	Moving cost across locations	See Table 2
$\overline{\epsilon_{0S}}$	0.0	Amenities - non-telec. suburb	Normalisation
$\overline{\epsilon_{1S}}$	0.0	Amenities - telec. suburb	Normalisation
$\overline{\epsilon_{0c}}$	0.044	Amenities - non-telec. center	See Table 2
$\overline{\epsilon_{1c}}$	0.039	Amenities - telec. center	See Table 2
Households - housing			
ω	1.015	Utility bonus from owning	Kaplan et al. (2020)
F^{sell}	7%	Selling cost	Kaplan et al. (2020)
δ	1.5%	Annual depreciation rate	Kaplan et al. (2020)
$h_{gridOwn}$	$[1.92; 2.46; 3.15; 4.03; 5.15]$	Grid for houses - owned	Kaplan et al. (2020)
$h_{gridRent}$	$[1.50; 1.92; 2.46; 3.15]$	Grid for houses - rented	Kaplan et al. (2020)
Households - labour			
η	-0.275	Taste for WFH	See Table 2
θ	0.82	Labour share in eff. units of labour	Valentinyi and 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 et al. (2023)
ρ	4.4	EOS WFH and WFO	Delventhal and 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	0.041	Technology construction sector	See Table 2
α_c	0.147	Housing supply elast. - center	Drayton et al. (2025)
α_s	0.153	Housing supply elast. - suburb	Drayton et al. (2025)
$\overline{L}$	0.311	Land permits (entire city area)	Kaplan et al. (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	0.003	Rental cies. operating cost	See Table 2
Financial sector			
r	0.03	Interest rate	Annual interest rate of 3%
ι	33%	Intermediation wedge	Kaplan et al. (2020)
λ_m	0.9	Debt collat. constraint	Greenwald (2018)

Notes: All values are reported at the yearly frequency. "n.d.c." stands for non-durable consumption, "telec." for telecommuters, "Pty." for productivity, and "EOS" for elasticity of substitution.

Table 2: Targeted Moments

Moment	Model	Data	Parameter	Source
Median net wealth over median income	4.91	4.91	β	W&A
WFH intensity (telec. workers)	0.15	0.15	η	UKTUS
Share of renters (London)	0.51	0.51	ψ	APS
Equilibrium house prices in center	1.0	1.0	Θ	Normalisation
Relative house prices suburb/center	0.63	0.63	$\overline{\epsilon_{1c}}$	Land Registry - EPC
Relative concentration of telec. - center	1.12	1.12	$\overline{\epsilon_{0c}}$	ASHE
Homeowner mobility rate (2-year)	0.06	0.06	F^{move}	EHS
Suburb-to-center labour income ratio	0.89	0.89	σ_ϵ	ASHE

Notes: Data are from the Wealth and Assets Survey (W&A), the UK Time Use Survey (UKTUS), the Annual Population Survey (APS), His Majesty's Land Registry Price Paid data, the Energy Performance Certificates dataset (EPC), the Annual Survey of Hours and Earnings (ASHE), and the English Housing Survey (EHS). telec. stands for telecommuters. "WFH intensity (telec. workers)" is the share of total working time spent at home by workers in telecommutable occupations. "Relative concentration of telec. - center" refers to the ratio of the share of telecommuters living in the center to the share of non-telecommuters living in the center. "Homeowner mobility rate (2-year)" is the share of homeowners who move out of their home over a two-year period.

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 0.036, and the fixed cost of relocating across locations is 0.011. These target the ratio of average labour income of households living in the suburbs to that of those living in the center, as well as the share of homeowners who sell their home and move over a two-year period. Finally, I calibrate location-specific commuting times using Transport for London (TfL) tube journey data from Larcom et al. (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.[10] 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, $\eta = -0.275$, 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 low, consistent with Barrero et al. (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 et al. (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 A.4.

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 et al. (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

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

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 et al. (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 slightly sparser version of the house size grids employed by the authors.[11] 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 et al. (2025). 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 supply elasticity is a well-documented issue in the UK, particularly in London. The operating cost of rental companies, $\phi = 0.003$, 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 et al. (2020). Inner London, corresponding to Zones 1 and 2 of the Underground, is allocated one-third of these permits.

3.2 Non-targeted Moments

This subsection presents how the model's stochastic steady state matches key moments that were not explicitly targeted during calibration. Table 3 reports these cross-sectional moments in both the model and the data.

The top panel displays moments relating to household location within the city. The model accounts well for the geographic distribution of households, even after conditioning on occupation.[12] The share of households living in the center is 41% in the data and 42% in the model. Similarly, the share of telecommuters living in the center is 43% in the data versus 44% in the model, while the share of non-telecommuters living in the center is 39% in both. The model also replicates the residential patterns of households across the income distribution, tracking relatively well the share of households living in the center within each labour income quintile.[13] 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 remote work.

[11] To reduce the computational burden, I use a 5-point grid rather than a 6-point one.

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

[13] The slight overestimation of the income gradient across locations stems from the fact that, in the model, labour income directly depends on where households live through hours worked and commuting costs. Consequently, by construction, lower labour incomes are overrepresented in the suburbs, and the opposite holds for higher labour incomes. The gradient is less steep and closer to the data when using resource quintiles defined as cash-in-hand within the model. See Appendix A.5.

The next panel displays the model's performance along the homeownership dimension. The model reproduces well the share of homeowners belonging to each income quintile.[14] Success in this dimension is once again crucial, as the model is used to study housing affordability. 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: 27% compared to 38% in the data. Finally, the average labour income of non-telecommuters amounts to 67% of that of telecommuters in the data, versus 70% in the model.

Table 3: Non-targeted Moments

Moment	Model	Data	Source
Location in the city			
Share of households living in center	0.42	0.41	ASHE
Share of telec. living in center	0.44	0.43	ASHE
Share of non-telec. living in center	0.39	0.39	ASHE
Share of bottom inc. quintile living in center	0.25	0.36	ASHE
Share of 2nd inc. quintile living in center	0.40	0.38	ASHE
Share of 3rd inc. quintile living in center	0.43	0.41	ASHE
Share of 4th inc. quintile living in center	0.44	0.44	ASHE
Share of top inc. quintile living in center	0.57	0.47	ASHE
Homeownership			
Share of bottom inc. quintile among own.	0.18	0.13	EHS
Share of 2nd inc. quintile among own.	0.14	0.18	EHS
Share of 3rd inc. quintile among own.	0.19	0.20	EHS
Share of 4th inc. quintile among own.	0.26	0.23	EHS
Share of top inc. quintile among own.	0.23	0.25	EHS
Share of owners in center	0.27	0.38	APS
Share of owners in suburb	0.65	0.60	APS
Income			
Labour income ratio non-telec./telec.	0.70	0.67	ASHE

Notes: "Telec." stands for telecommuters, "non-telec." for non-telecommuters, "inc." for income, and "own." for owners. "Share of bottom inc. quintile living in center" refers to the share of households in the bottom income quintile who live in the center. "Share of bottom inc. quintile among own." refers to the share of homeowners who belong to the bottom income quintile.

3.3 Decision Rules

To understand the mechanisms at play in the model, it is useful to examine households' decision rules. Figure 1 plots the probability that a household chooses to live

[14] Here again, the non-monotonicity between the bottom two quintiles and the top two quintiles results from the fact that lower labour incomes are mechanically overrepresented in the suburbs, where housing is cheaper, with the opposite holding for higher labour incomes. Appendix A.5 recomputes these moments by quintiles of cash-in-hand within the model. In this case, the share of owners within each resource quintile becomes monotonically increasing and closely matches the data.

in the center as a function of liquid wealth.[15]

Panel a displays this decision rule for a household that begins the period without owning any real estate, located in the center (in blue) and in the suburb (in yellow).[16] First, the probability of choosing the center is higher for households already living there, reflecting the moving costs associated with relocating across neighborhoods. Second, we observe that the probability of choosing to live in the center is non-monotonic in liquid wealth. This arises because the probability 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 of 12—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 becomes steeper.

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 yellow).[17] 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, in addition to moving costs, the suburban homeowner would need to sell their property in order to relocate, incurring further transaction costs. Moreover, the gap between the two probabilities narrows as liquid wealth increases. This reflects the fact that, since selling costs are a fixed share of the property value, they are particularly binding at lower wealth levels and become less of a deterrent as households accumulate more liquid assets. This pattern arises from the non-convex nature of the adjustment costs, and highlights an interaction between the structure of those costs and the distribution of wealth

4 Results: the Work-from-Home Experiment

4.1 Change in Preferences

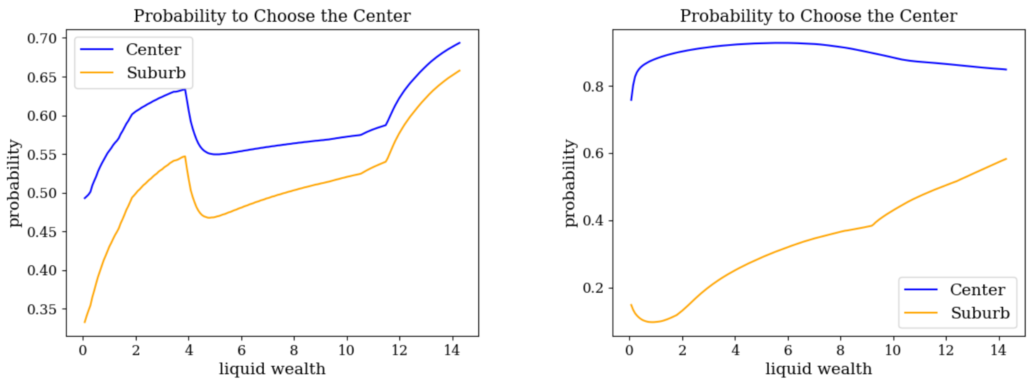
I now simulate the impact of a permanent shift in the preference parameter associated with remote work. In the baseline, the WFH preference parameter is calibrated to

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

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

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

Figure 1: Decision Rules: Probability to Choose the Center



(a) Non-homeowners

(b) Homeowners

Notes: Policy functions for households previously living in the center are shown in blue, and for those previously living in the suburb in yellow. Households are employed in a telecommutable occupation and have median income. Homeowners have median housing wealth and no collateralized debt. Liquid wealth is normalized by average biannual income in the economy.

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 56%—equivalent to slightly more than 2.5 days of remote work per week.[18] 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.

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. (2025); Sedlácek and Shi (2024)) and survey evidence to document a rise in workers' valuation of remote work (e.g., Chen et al. (2023); Zarate et al. (2024); Bick et al. (2023); Barrero et al. (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 work experiences and a substantial decline in the stigma previously associated with WFH. 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. The authors also 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%. Similarly, according to LinkedIn job posting data from February 2022, remote positions represented fewer than 20% of paid listings yet captured over 50% of total applicant interest.[19]

[18]For workers in telecommutable occupations.

[19]Source: "In a First, Remote Jobs Attract a Majority of Applications on LinkedIn", Greg Lewis,

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. However, technology alone cannot plausibly account for such a dramatic shift in working arrangements. 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.

4.2 WFH and Housing Demand

The rise in remote work reshaped housing demand and its allocation within the city. Figure 2 plots the evolution of house prices in the center (in blue) and in the suburb (in yellow) following the change in WFH preferences. In the long run, house prices increase throughout the city, but more so in the suburb. This change in housing demand is driven by workers in telecommutable occupations.

Figure 2: Changes in House Prices

Notes: House prices normalized to 1 at $t = 0$. WFH preference parameter changes at $t = 1$.

Following the shift in preferences, workers who can work remotely spend a larger share of their time working from home. This has two consequences. First, they require more space for a home office, raising housing demand throughout the city.

April 7, 2022.

Second, they commute less frequently to the office. Since suburban housing is cheaper, remote workers relocate to purchase larger, more affordable properties outside the city center. Consequently, housing demand rises more in the suburb than in the center, leading to a relative appreciation of suburban prices. In other words, the penalty for living farther from the city center decreases. The next section examines whether this testable prediction holds in the data for London, allowing us to assess the importance of remote work in accounting for the spatial reallocation of housing demand.

This reallocation of housing demand is further reflected in telecommuters' tenure and neighborhood choices. The upper panel of Table 4 reports these choices both before the rise in WFH and in the long run. The share of telecommuters who own a home in the suburb increases from 46% to 63%, while the homeownership rate in the center remains stable. Overall, the share of telecommuters living in the suburb rises by 11 percentage points in the long run. This suburbanization of telecommuters is mirrored by a compositional shift in the city center, where the share of non-telecommuters rises from 39% to 52%.

Table 4: Location and Tenure Allocations

Share of households	Before WFH	After WFH
Telecommutable occ.		
Own - Center	22%	22%
Own - Suburb	46%	63%
Rent - Center	23%	11%
Rent - Suburb	10%	4%
Non-telecommutable occ.		
Own - Center	1%	2%
Own - Suburb	30%	9%
Rent - Center	38%	50%
Rent - Suburb	31%	39%

Notes: *Before WFH* refers to the initial steady state; *After WFH* refers to the steady state following the rise in remote work. *Occ.* stands for occupations.

The transition path of house prices highlights differences in the timing of the rise in housing demand across locations. In the period immediately following the shift in WFH preferences, prices rise in the suburb and fall in the center, reflecting who the new movers in each neighborhood are. Telecommuters seeking larger properties to facilitate working from home tend to be sufficiently wealthy to purchase without delay, so the increase in suburban housing demand is immediate and prices adjust accordingly. In the center, by contrast, housing demand initially dips. This dip is explained by the behavior of non-telecommuters. Prior to the shift in working arrangements, the vast majority of non-telecommuters with real estate own homes in the suburb.[20] These are precisely the properties that appreciate most with the rise in remote work. Facing increased demand from wealthy telecommuters, a share of these non-telecommuters sell their suburban homes, realize capital gains, and relocate to the center. However, since the price difference between the two locations is large, the

[20]Suburban homeowners account for 97% of non-telecommuters with real estate.

capital gains from selling are typically insufficient to purchase in the center. As a result, these households transition to renting.

Finally, the dynamics of liquid wealth help explain the medium-run evolution of house prices. When WFH preferences shift, telecommuters' housing demand jumps and many of these households purchase property by drawing down their liquid savings. Since housing is a durable good, this surge in immediate adjustment suppresses demand for new housing in subsequent periods. Moreover, telecommuters who depleted their liquid wealth at the time of the shock must subsequently rebuild their savings. Together, these forces drive a gradual decline in house prices in both locations in the medium run. House prices begin rising again only as telecommuters' liquid wealth recovers.[21]

4.3 Distributional Implications

The shift in telecommuters' housing demand—and its geographic reallocation—has significant consequences for other households. Non-telecommuters tend to sit at the bottom of the income and wealth distributions.[22] When purchasing a home, they typically do so in the suburb, where housing is more affordable. Yet the relative appreciation of suburban properties prices them out of homeownership altogether. The housing market thus acts as a transmission channel, carrying the effects of WFH from those who can partake in it to those who cannot. Through general equilibrium, the remote work decisions of one segment of the workforce ripple outward to the rest of the economy.

Table 4 illustrates this dynamic. The share of telecommuters who own a home in the suburbs rises from 46% to 63%, while homeownership rates in the center remain stable—implying a substantial overall increase in homeownership among telecommuters. Among non-telecommuters, by contrast, the homeownership rate falls by 20 percentage points in the long run, a decline concentrated entirely in the suburbs. The share of non-telecommuters who rent in the center rises from 38% to 50% and from 31% to 39% in the suburb. The right panels of Figure 3 display the housing wealth distributions for telecommuters (top) and non-telecommuters (bottom). For telecommuters, the distribution shifts markedly rightward, from the initial steady state before the rise in WFH (blue) to the new steady state after the rise in WFH (orange). The opposite holds for non-telecommuters, where the most striking feature is a sharp rise in the mass of households with zero housing wealth.

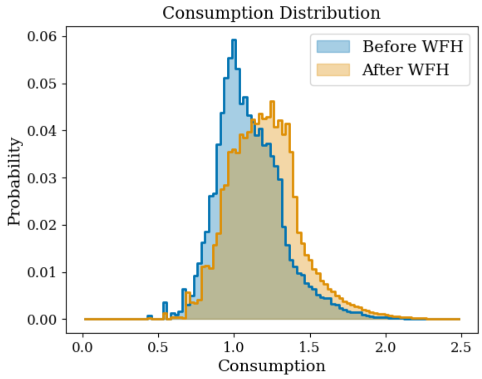
Table 5 further illustrates this mechanism by reporting location and tenure probabilities across the two steady states for the marginal non-telecommuter buyer.[23]

[21] Figure 5 in the Appendix B plots the evolution of liquid assets for telecommuters and non-telecommuters. Non-telecommuters' liquid assets rise sharply in the periods following the shock, yet this has little bearing on house prices, as this group mainly relocated to urban areas where owner-occupied housing remains unaffordable for them.

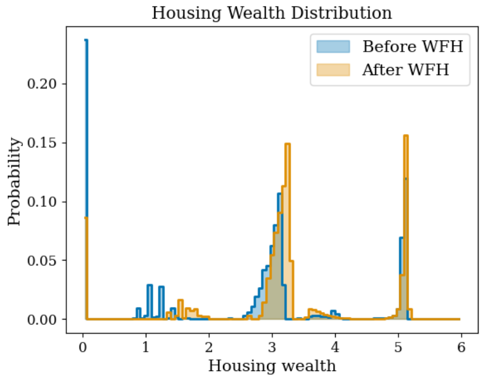
[22] For instance in London in 2019, the average weekly labor income of the non-telecommuters was 67% of that of telecommuters (ASHE).

[23] 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 at a lower level of liquid wealth or income. This household enters the period with no real estate holdings and liquid wealth around 70% above the population median.

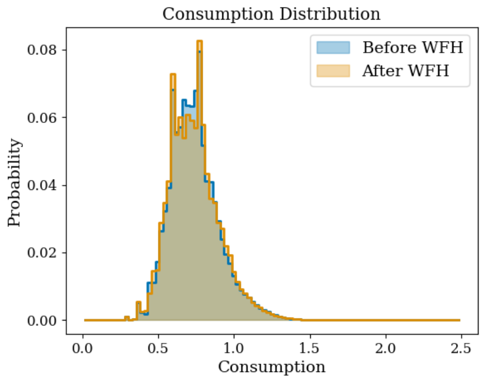
Figure 3: Distributions in the Two Steady States



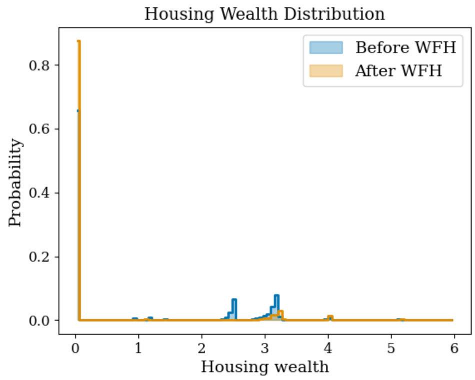
(a) Consumption (Telecommuters)



(b) Housing Wealth (Telecommuters)



(c) Consumption (Non-telecommuters)



(d) Housing Wealth (Non-telecommuters)

Notes: Non-durable consumption and housing wealth distributions in the baseline steady state (in blue) and in the steady state following the rise in WFH (in yellow). The discontinuous shape of the housing wealth distributions reflects the discrete housing grid.

Before the rise in WFH, it purchases a home in the suburb with probability 0.62 and rents in the center with probability 0.38. In the new steady state, however, the same household is entirely crowded out of the owner-occupied market: it now rents in the suburb with probability 0.59 and in the center with probability 0.41. The surge in telecommuters' housing demand in the suburbs, and the resulting displacement of lower-wealth buyers, resembles a gentrification shock—one that affects the entire urban periphery.

More broadly, the rise of WFH gave birth to a *tele-premium*—an extra benefit accruing to workers in occupations where remote work is feasible. The first panel of Table 6 documents this premium by reporting the ratio of average consumption, income, housing wealth, and liquid wealth of telecommuters to that of non-telecommuters, before and after the shift to remote work. Across most dimensions, the *tele-premium* has grown substantially. The effect is most pronounced for housing wealth: telecommuters' average housing wealth was less than three times that of non-telecommuters before the shift, but this ratio climbs to 8.38 afterward—a direct consequence of suburban price appreciation and the crowding out of marginal non-telecommuter buyers

Table 5: 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	0.62	0.38	0.0
After WFH	0.0	0.0	0.41	0.59

Notes: The marginal non-telecommuter buyer is a household who begins the period without owning any real estate and has liquid wealth 72% above the population median. *P.* stands for probability.

documented above.

Inequality across occupations also widens along the income and consumption dimensions. In the long run, non-telecommuters' labour income rises by 1%, driven by lower commuting costs for those able to relocate to the center, while telecommuters' average labour income rises by 5%, reflecting both savings in commuting time from working at home and some degree of complementarity between working from home and working at the office. This is consistent with empirical evidence for the UK in Polo et al. (2024), where the authors exploit variation in remote work exposure across occupations around the Covid-19 pandemic and find that real wage growth between 2019 and 2022 was 3 percentage points higher for occupations in the top quintile by WFH share relative to the bottom, with roughly half of this effect attributable to hours worked.[24] Telecommuters' income gains translates into higher consumption: as shown in panel (a) of Figure 3, their consumption distribution shifts rightward after the rise in WFH. No such shift is observed for non-telecommuters. Finally, the rise in remote work reduces long-run liquid wealth inequality, as telecommuters rebalance their portfolios toward real estate while non-telecommuters—crowded out of homeownership—do the opposite.

The lower parts of Table 6 present several inequality measures for the overall population. Consumption and income inequality increase across all reported 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 center. Following the shift to WFH, the relative value of these 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 long-run is both wealthier and more homogeneous, contributing to the observed reduction in housing wealth inequality along the intensive margin.

4.4 Welfare

The gains associated with the rise in remote work span the entire population of telecommuters, as illustrated by the rightward shifts in their housing wealth and

[24]In another European context, Li et al. (2026) use French administrative data to document a 6% remote work wage premium. Pabilonia and Vernon (2025) reports comparable findings for the US.

Table 6: Consumption, Income, Housing, and Liquid Wealth Inequality

Tele-premium	Before WFH	After WFH
Consumption	1.49	1.63
Income	1.43	1.49
Housing wealth	2.70	8.38
Liquid wealth	1.26	1.10
Overall Inequality	Before WFH	After WFH
Consumption		
90th/10th ptile	2.13	2.30
90th ptile/median	1.42	1.46
Income		
90th/10th ptile	2.20	2.24
90th ptile/median	1.49	1.48
Housing wealth		
90th ptile/median	3.49	3.11
Liquid wealth		
90th/10th ptile	12.81	13.58
90th ptile/median	2.51	2.31
Tenure Inequality	Before WFH	After WFH
Consumption		
owners/renters	1.38	1.59
Income		
owners/renters	1.10	1.33
Liquid wealth		
owners/renters	1.67	1.51

Notes: *Tele-premium* refers to the ratio of the average consumption, income, housing, and 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. The bottom panel relates to ownership status, reporting the ratio of average consumption, income, and liquid wealth of homeowners to that of renters.

consumption distributions in Figure 3. The picture is more ambiguous for non-telecommuters, however. How do the increase in inequality across occupations and the change in housing demand impact workers who can't work from home?

Table 7 reports the welfare changes experienced by non-telecommuters following the rise in remote work. Welfare is measured as a consumption equivalent variation—the additional consumption households would need after the rise in WFH to be as well-off as before, expressed as a percentage of current consumption. Positive values therefore indicate welfare losses. Computing a utility-based welfare measure is not straightforward for telecommuters, as this group experiences a change in the preference parameter for WFH over the period. This issue does not arise for non-telecommuters, who cannot work from home and whose preferences therefore remain unchanged, making a utility-based welfare measure a clean and consistent metric for this group.

The first column of Table 7 reports welfare changes in the long run, comparing the low-WFH and high-WFH steady states. Overall, non-telecommuters experience a decline in welfare: they would need a consumption boost of 0.47% in the second steady state to be indifferent to the rise in remote work. The welfare loss is more pronounced for renters, who would require a 0.51% consumption equivalence boost and 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, while higher house prices make it harder for these households to access homeownership. Somewhat surprisingly, homeowners also experience a welfare loss of 0.18% in consumption equivalence, despite the appreciation in the value of their property. This reflects a combination of factors: decreased flexibility in relocating or changing homes (house prices and rents increased across all areas of the city), a higher user cost of housing (maintenance costs are proportional to house prices), 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 a fixed-share of the value of the property sold) are especially discouraging for low-income and low-liquid wealth owners, who are disproportionately represented among non-telecommuters.

The second column of Table 7 reports welfare changes for non-telecommuters including the transition period. This distinction matters for two reasons. First, prices across locations did not rise immediately or linearly during the transition. Second, prior to the rise in WFH, non-telecommuters who own real estate held property predominantly in the suburbs—precisely the locations that appreciated the most following the shift in WFH preferences. As a result, these households may experience welfare gains in the short run, making it crucial to account for initial conditions when assessing the full welfare impact.

Overall, incorporating the transition period dampens non-telecommuters' welfare losses. For renters, this is because house prices and rents take time to reach their new steady-state values, particularly in the city center. For homeowners, welfare losses are milder than in the long run, as some households benefit from rising prices by selling their property. That said, non-telecommuters still experience welfare losses on average. For homeowners, this again reflects the interaction between non-convex adjustment costs and the wealth distribution.

Table 7: Welfare of the Non-telecommuters (Consumption Variation)

Non-telecommuters	Long-run	Including Transition
All non-telecommuters	**0.47%**	**0.19%**
Renters	**0.51%**	**0.21%**
Renters - Center	0.48%	0.19%
Renters - Suburb	0.56%	0.24%
Owners	**0.18%**	**0.06%**
Owners - Center	0.19%	0.09%
Owners - Suburb	0.17%	0.05%

Notes: Welfare of the non-telecommuters. Consumption equivalence variations measure the percentage increase in consumption required to keep households' utility unchanged after the rise in remote work. Positive values indicate welfare losses. the first column computes welfare changes in the long-run comparing the high WFH steady state to the baseline economy. The second column includes the transition period.

4.5 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.[25] 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 replicate 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 in which the supply of land permits in the center increases by 5%. I then compare the outcomes of this policy experiment to those of the baseline. Expanding the availability of central land permits not only reduces house prices in the center by 1% in the long run, but also dampens the rise in suburban house prices to just 0.5%.

Table 8 presents 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 policy does not succeed in enabling non-telecommuters to buy in the center — given the large price differential between the suburb and the center, homeownership in

[25]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.

the center remains especially out of reach for this group. Nevertheless, the share of non-telecommuters who own in the suburb is 4 percentage points higher than in the baseline, as the more modest rise in suburban prices makes ownership there more attainable. Telecommuters, on the other hand, take advantage of the lower prices in the center and are more likely to own there under the policy.

Table 8: Location and Tenure Allocations (Policy Experiment)

Share of households	Before WFH	After WFH	After WFH (Pol.)	Change (Pol.)
Telecommutable occ.				
Own - Center	22%	22%	25%	$+3pts$
Own - Suburb	46%	63%	61%	$-2pts$
Rent - Center	23%	11%	10%	$-1pt$
Rent - Suburb	10%	4%	4%	–
Non-telecommutable occ.				
Own - Center	1%	2%	2%	–
Own - Suburb	30%	9%	13%	$+4pts$
Rent - Center	38%	50%	48%	$-2pts$
Rent - Suburb	31%	39%	36%	$-3pt$

Notes: Columns 1 and 2 replicate the results from Table 4. 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.

Finally, lower house prices and rents in the center, combined with a much milder rise in the suburb, reduce housing expenses — a development that is particularly beneficial for households at the bottom of the income and wealth distributions. Table 9 illustrates this point by reporting the welfare changes experienced by non-telecommuters following the rise in WFH under 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 indicate welfare losses, while negative values reflect welfare gains. On average, non-telecommuters experience welfare gains under the policy. These gains are most pronounced for renters, amounting to 0.1% of their current consumption. In contrast, homeowners in the center experience a modest welfare loss, due to the decline in the value of their housing assets.

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.

5 Empirical Evidence

In the model, the main result—that the housing market acts as a bridge channeling the effects of WFH to workers who cannot work remotely, with implications for household allocation, inequality, and welfare—is driven by the relative change in house prices across locations, namely the decline in the commuting penalty. This key prediction is testable in the data. I use house price data for the London metropolitan area to first

Table 9: Welfare of the Non-telecommuters Policy Experiment (Consumption Variation)

Non-telecommuters	Baseline	Policy Experiment
All non-telecommuters	**0.47%**	**-0.09%**
Renters	**0.51%**	**-0.10%**
Renters - Center	0.48%	−0.10%
Renters - Suburb	0.56%	−0.10%
Owners	**0.18%**	**-0.02%**
Owners - Center	0.19%	0.02%
Owners - Suburb	0.17%	−0.03%

Notes: Welfare of non-telecommuters. Consumption equivalence variations measure the percentage increase in consumption required to keep households' utility unchanged following the rise in remote work. Positive values indicate welfare losses and negative values welfare gains. The first column replicates the results from Table 7. In the second column, consumption equivalence variations are computed between the baseline steady state and a counterfactual steady state featuring a 5% increase in the supply of land permits in the center.

verify that the distance penalty has indeed declined since the rise of remote work, and second to assess the relative importance of remote work in the changing housing demand across the city.

5.1 Data

The data used for this section are at the property level and provide a mapping between house prices and detailed dwelling characteristics. These data come from two 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. I then merge the Land Registry 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 can be matched to an EPC record. The merging procedure uses property addresses.[26]

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.[27] Consequently, in the empirical analysis, I treat March 2020 as the beginning of the rise in working from home. 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.

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

[27] Similarly, Hansen 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.

Table 10 provides descriptive statistics from the merged housing dataset. The sample covers the period from January 2016 to June 2022, just before the onset of the UK's double-digit inflation episode and the Bank of England's rate hikes above 1%. Table 10 reports the number of registered property transactions, the average transaction price, and the average 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.

Table 10: Descriptive Statistics – House Prices (London)

	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

Notes: The sample covers January 2016 to June 2022. To mitigate the influence of outliers, the top 1% of observations in prices and property size are excluded.

5.2 Appreciation of Suburban Properties

The first panel of Figure 4 displays changes in house prices 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 in each local authority between the year before COVID-19 and the most recent year of data (July 2021 to June 2022). 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 line is added to each plot. Panel (a) reveals a clear positive relationship between house price appreciation and distance from the city center.

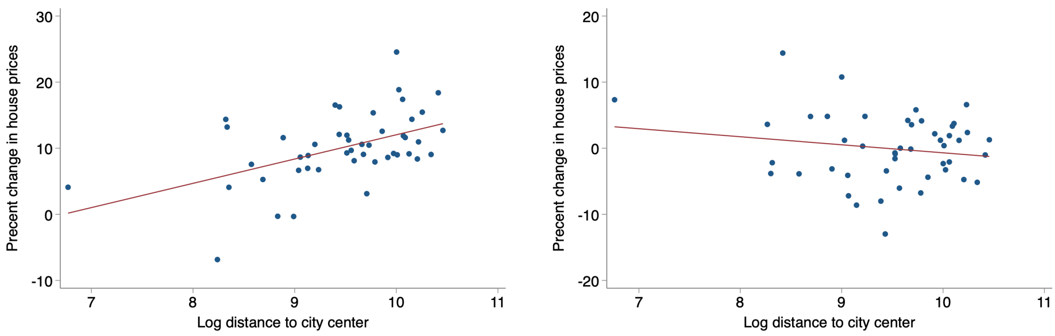
In the spirit of a placebo test, panel (b) plots changes in house prices between 2017 and 2019 against the logarithm of distance to the city center. In this placebo specification, no positive relationship between property appreciation and distance from the Bank of England is observed.

The finding that properties located further out appreciated faster since the pandemic and the rise in remote work is not London specific. Ramani and Bloom (2022) 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 city centers and the rise in demand for peripheries.

5.3 Hedonic Pricing Schedule

I now estimate the impact of proximity to the city center on house prices to 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

Figure 4: Growth in House Prices as a Function of Distance from the City Center



(a) House Prices

(b) House Prices (Placebo)

Notes: Each dot represents one of London's local authorities (e.g., Camden, Hackney). In panel (a), the x-axis plots the change in average house prices between the year prior to COVID-19 and the most recent year of available data (July 2021 to June 2022). In the placebo specification (panel (b)), the x-axis plots changes in house prices 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 and property size (in square meters) are excluded. A linear fitted line is added to each plot.

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 log of the transaction price 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 status, and an indicator for whether the property is newly built. These controls account for neighborhood and housing quality heterogeneity.

Table 11 reports estimates of the impact of log distance to the city center on log house prices. Column 1 corresponds to the main specification described above, while column 2 presents 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 coefficient between distance and post-WFH period is expected to be statistically insignificant.

In both specifications, the coefficient on distance is 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

Table 11: Impact of Distance to City Center on House Prices

	(1) log_price	(2) log_price
log_dist	-0.267***	-0.285***
	(0.0355)	(0.0339)
log_dist after WFH	0.0226**	0.0108
	(0.0071)	(0.0086)
Observations	723,479	440,714
Adj. R-squared	0.568	0.542
Placebo		✓
Monthly FE	✓	✓
Local authority FE	✓	✓
Property controls	✓	✓
SE	Clust. at LA	Clust. at LA

Standard errors in parentheses

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

Notes: 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. Column 1 uses data from January 2016 to June 2022. The placebo specification in column 2 uses data from January 2016 to December 2019. To mitigate the influence of outliers, I drop the top and bottom 1% of observations in prices and property size. Standard errors are clustered at the local authority level.

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 coefficient in Table 11 reports the interaction effect between the post-February 2020 period and distance to the city center. The interaction coefficient in the placebo specification of Column 2 is reassuringly insignificant. In the non-placebo specification (column 1) however, this coefficient is 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 7.7%. This reflects a flattening of the distance gradient, or equivalently, a decline in the commuting penalty. This result is consistent with the driving mechanism in the model.

Several robustness exercises are presented in Appendix C.1, including heterogeneity analysis by house size, an interaction term between size and distance, a room-count dummy in place of square meters, and a size coefficient allowed to vary after February 2020. The results remain consistent with the baseline estimates. Appendix C.2 presents an alternative specification in which the distance coefficients vary monthly, again pointing to a decline in the commuting penalty. Finally, Appendix D replicates the analysis using rents rather than house prices, and the results are once more consistent with a decline in the distance penalty in the London rental market following the rise in WFH.

5.4 Importance of WFH

Beyond assessing the empirical validity of a decline in the distance penalty, this exercise also allows us to gauge the importance of the rise in remote work in accounting for the spatial reallocation of housing demand across London. Table 12 reports changes in the distance penalty in the model[28] and in the data (from the hedonic pricing schedule).

We find that the model accounts for approximately half of the observed flattening of the distance gradient, highlighting that the shift toward remote work is a key driver of the spatial reallocation of housing demand. The remaining gap may reflect factors not captured by the model, such as the relocation of amenities from city centers to suburbs, or shifts in neighborhood preferences following the pandemic — including aversion to density and increased demand for green spaces.

Table 12: Change in Distance Penalty

	Model	Data	Share Explained by Model (%)
Change in distance penalty (%)	-7.7	-3.7	49

Notes: Changes in the distance penalty in the model and in the data. In the model, the change in the distance penalty reflects the change in the price difference between suburban and central locations, comparing the year before the rise in WFH to two years after. In the data, the change in the distance penalty comes from the hedonic pricing schedule.

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. 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. 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. I show that the housing market acts as the bridge through which the effects of WFH spill over to workers who cannot telecommute. The relative appreciation of suburban properties is the key force underlying the theoretical results, making its empirical validation particularly

[28] Measured as the change in the price differential between suburban and central locations — comparing the year before the rise in remote work to two years after.

important. Using detailed real estate data for London, I find that, since the rise of remote work, the penalty for distance from the city center has fallen by 7.7%. Remote work alone can account for half of this decline. 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.

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A Model Details, Numerical Implementation, and Calibration

A.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.

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

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

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

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

A.2 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 $\{c^h, c^n, b'^h, b'^n, h'^h, h'^n, m'^h, m'^n,$ $(n^H)^h, (n^H)^n, (n^O)^h, (n^O)^n, j'^h, j'^n, keep^h, sell^h, sellandbuy^h, sellandrent^h, buy^n, rent^n,$ $move^h, move^n\}$, 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 $\{c^h, c^n, b'^h, b'^n, h'^h,$ $h'^n, m'^h, m'^n, (n^H)^h, (n^H)^n, (n^O)^h, (n^O)^n, j'^h, j'^n, keep^h, sell^h, sellandbuy^h,$ $sellandrent^h, buy^n, rent^n, move^h, move^n\}$.

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_j^h and the equilibrium quantity of houses satisfies:

$$I_j^h - \delta H_j + \int_{\mathbb{X}^h} hsell^h(x^h)\, d\mu^h = \delta H_j^r + \int_{\mathbb{X}^n} h'^n(x^n) j'^n(x^n) buy^n(x^n)\, d\mu^n + \int_{\mathbb{X}^h} h'^h(x^h) j'^h(x^h) sellandbuy^h(x^h)\, d\mu^h$$

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:

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

where the first two terms on the right-hand side represent expenditures on the final consumption good. The next terms capture transaction costs incurred by households who sell their homes and moving costs paid by those who relocate across locations. 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.

A.3 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 500-point grids for cash-on-hand and liquid assets, an 5-point grids for collateralized debt and 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^{-7}. 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. The Jacobian is computed using the fake news algorithm of Auclert et al. (2021).

A.4 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:

$$log(y_{it}) = Z'_{it}\beta + \tilde{y_{it}}$$

$$\tilde{y_{it}} = P_{it} + \epsilon_{it}$$

$$P_{it} = \tilde{\rho} P_{it-1} + u_{it}$$

$$\epsilon_{it} \sim i.i.d, \quad u_{it} \sim \mathcal{N}(0, \sigma_u^2)$$

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:

$$\frac{Cov(\tilde{y_{it}}, \tilde{y_{it-2}})}{Cov(\tilde{y_{it}}, \tilde{y_{it-1}})} = \tilde{\rho}$$

$$Cov(\tilde{y_{it}}, \tilde{y_{it-1}}) = \tilde{\rho} * \sigma_P^2$$

$$(1 - \tilde{rho}^2) * \sigma_P^2 = \sigma_u^2$$

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.

A.5 Non-targeted Moments

Table 13: Non-targeted Moments (Resources)

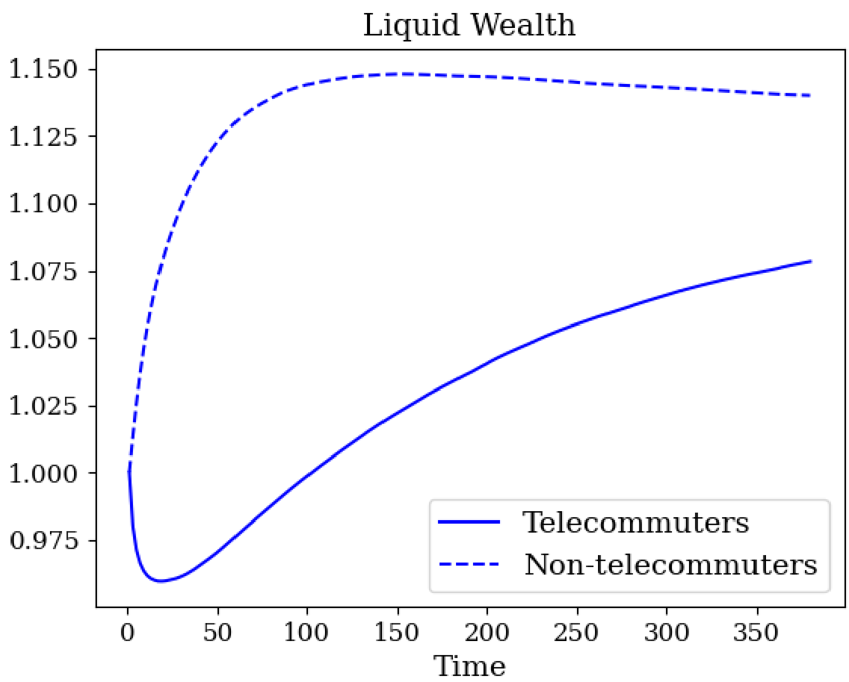
Moment	Model	Data	Source
Location in the city			
Share of bottom res. quintile living in center	0.34	0.36	ASHE
Share of 2nd res. quintile living in center	0.34	0.38	ASHE
Share of 3rd res. quintile living in center	0.36	0.41	ASHE
Share of 4th res. quintile living in center	0.41	0.44	ASHE
Share of top res. quintile living in center	0.64	0.47	ASHE
Homeownership			
Share of bottom res. quintile among own.	0.12	0.13	EHS
Share of 2nd res. quintile among own.	0.16	0.18	EHS
Share of 3rd res. quintile among own.	0.18	0.20	EHS
Share of 4th res. quintile among own.	0.25	0.23	EHS
Share of top res. quintile among own.	0.29	0.25	EHS

Notes: "Res." stands for resources and "own." for owners. Resources are measured as cash-in-hand in the model and as income in the data. "Share of bottom res. quintile living in center" refers to the share of households in the bottom resource quintile who live in the center. "Share of bottom res. quintile among own." refers to the share of homeowners who belong to the bottom resource quintile.

B Additional Results

Figure 5 shows the average liquid wealth of telecommuters (solid line) and non-telecommuters (dashed line) over the transition period.

Figure 5: Changes in Liquid Wealth



Average liquid wealth normalized to 1 at t = 0. WFH preference parameter changes at t = 1.

C Additional Empirical Results

C.1 Robustness for Hedonic Price Schedule

Table 14 explores the heterogeneity in the flattening of the distance gradient by property size. Columns 1 and 2 focus on properties with sizes below and above the median, respectively. 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.

Table 19 provides several robustness checks for the hedonic price schedule estimated in Section 5. Column 1 reports the baseline specification from Section 5. 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. The results are consistent with those of the baseline specification.

C.2 Alternative Hedonic Specification: Monthly Coefficients (House Prices)

Equation (1) in the main text evaluates the total change in the importance of distance in determining house prices over the entire post-pandemic period. Another interesting

Table 14: Impact of Distance to the City Center on House Prices, by Property Size

	(1) log_price	(2) log_price
log_dist	-0.241***	-0.295***
	(0.0330)	(0.0416)
log_dist after WFH	0.0056	0.0350***
	(0.0069)	(0.0099)
Observations	365,422	358,057
Adj. R-squared	0.391	0.569
Below median size	✓	
Above median size		✓
Monthly FE	✓	✓
Local authority FE	✓	✓
Property controls	✓	✓
SE	Clust. at LA	Clust. at LA

Standard errors in parentheses

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

Notes: 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. Column 1 includes properties smaller than the median, while column 2 includes properties larger than the median. To mitigate the influence of outliers, I drop the top and bottom 1% of observations in prices and property size. Standard errors are clustered at the local authority level.

Table 15: Impact of Distance to City Center on House Prices: Robustness

	(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

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

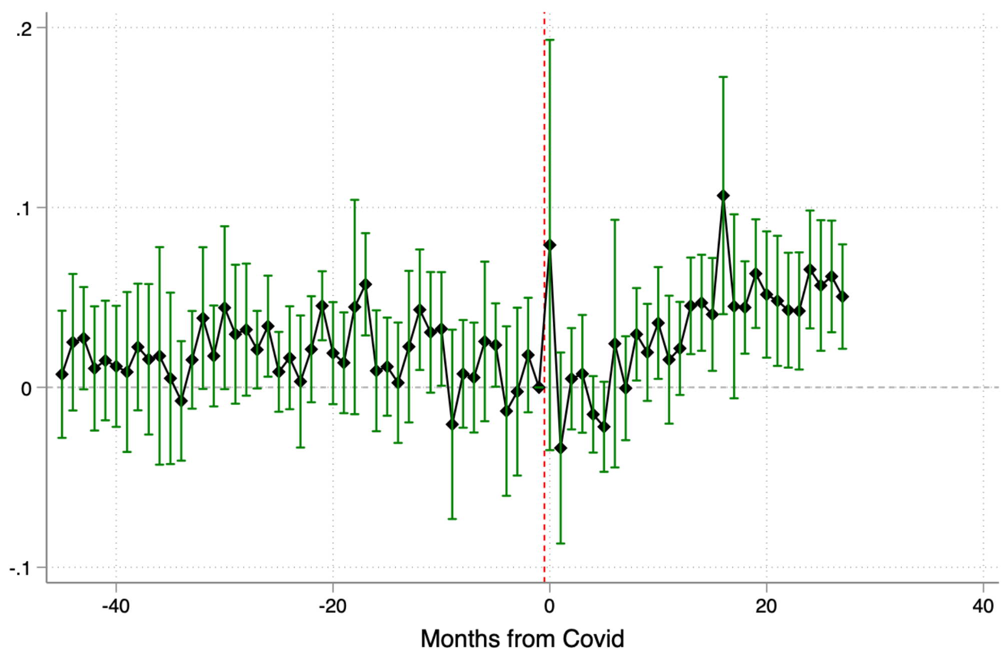
Notes: This table reports results from OLS regressions of Equation (1), using the log of house prices as the dependent variable. Property-level controls include the lag of the average house price in the local authority, property type, energy rating, energy efficiency, presence of a fireplace, leasehold 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.

exercise is to examine the distance gradients for each month within the 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 house prices in each month relative to the baseline period of February 2020 and are plotted in Figure 6. 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 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.

Figure 6: Month-Specific Distance Coefficients: House Prices (London)



(a) Distance Coefficients on House Prices

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

D Empirical Evidence: Rents

This appendix replicates the empirical analysis of Section 5 using rental data. The results show that the flattening of the distance gradient documented for house prices also holds for rents, suggesting that the decline in the commuting penalty is a broad phenomenon affecting both the owner-occupier and rental markets.

D.1 Data

Because this paper also examines the impact of remote work on renters, I complement the Land Registry data with 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. As with the house price data, the rental listings are merged with the EPC dataset using property addresses to obtain dwelling characteristics.

Table 16 provides descriptive statistics for the rental sample, which covers the period from 2016 to 2021. 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.

Table 16: Descriptive Statistics – Rents (London)

	2016	2017	2018	2019	2020	2021
# 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

Notes: The sample covers January 2016 to December 2021, based on rent data availability. To mitigate the influence of outliers, the top 1% of observations in rents and property size are excluded.

D.2 Appreciation of Suburban Properties

Figure 7 replicates Figure 4 for rents. Panel (a) plots changes in rents between the year before COVID-19 and 2021 against the logarithm of distance to the city center, while panel (b) presents the corresponding placebo specification using changes between 2017 and 2019. As with house prices, panel (a) reveals a clear positive relationship between rent growth and distance from the city center, while no such relationship is observed in the placebo.

D.3 Hedonic Pricing Schedule

Table 17 replicates the hedonic pricing schedule of Table 11 using log rents as the dependent variable. Column 1 corresponds to the main specification and column 2 to the placebo test.

The results mirror those obtained for house prices. The coefficient on distance is negative and the interaction with the post-February 2020 period is positive and significant, confirming that the distance penalty also declined in the rental market. As with house prices, the placebo interaction coefficient is not statistically significant.

Table 18 explores heterogeneity by property size for rents. In contrast to house prices, the flattening of the distance gradient is present for both small and large rental properties. Table 19 replicates the robustness checks of Table 14 using log rent as the dependent variable. The results are consistent with those of the baseline specification reported above. Finally, Figure 8 replicates Figure 6 for rents. As with house prices, no pre-trend is observed before February 2020, while the distance coefficients become positive and significant in the later part of the sample.

Table 17: Impact of Distance to City Center on Rents

	(1) log_rent	(2) log_rent
log_dist	-0.182***	-0.185***
	(0.0281)	(0.0264)
log_dist after WFH	0.0476***	-0.0003
	(0.0046)	(0.0033)
Observations	620,681	433,459
Adj. R-squared	0.661	0.662
Placebo		✓
Monthly FE	✓	✓
Local authority FE	✓	✓
Property controls	✓	✓
SE	Clust. at LA	Clust. at LA

Standard errors in parentheses

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

Notes: This table reports results from OLS regressions of Equation (1), using the log of listed rents 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. Column 1 uses data from January 2016 to December 2021. The placebo specification in column 2 uses data from January 2016 to December 2019. To mitigate the influence of outliers, I drop the top and bottom 1% of observations in rents and property size. Standard errors are clustered at the local authority level.

Table 18: Impact of Distance to the City Center on Rents, by Property Size

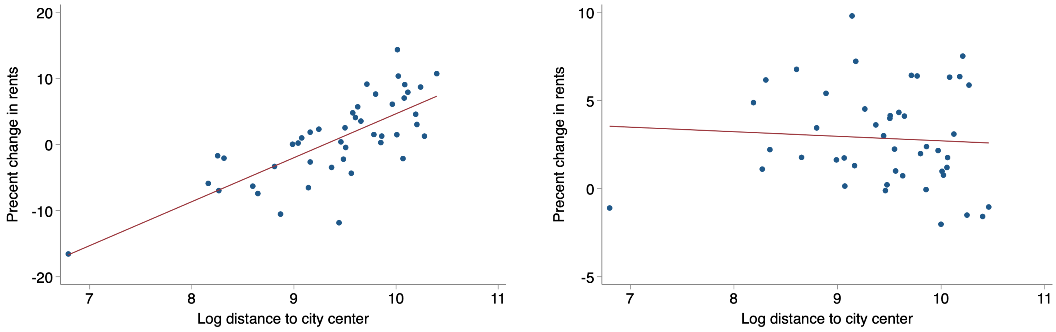
	(1) log_rent	(2) log_rent
log_dist	-0.164***	-0.215***
	(0.0279)	(0.0263)
log_dist after WFH	0.0473***	0.0452***
	(0.0052)	(0.0035)
Observations	316,406	304,275
Adj. R-squared	0.617	0.570
Below median size	✓	
Above median size		✓
Monthly FE	✓	✓
Local authority FE	✓	✓
Property controls	✓	✓
SE	Clust. at LA	Clust. at LA

Standard errors in parentheses

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

Notes: This table reports results from OLS regressions of Equation (1), using the log of listed rents 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. Column 1 includes properties smaller than the median, while column 2 includes properties larger than the median. To mitigate the influence of outliers, I drop the top and bottom 1% of observations in rents and property size. Standard errors are clustered at the local authority level.

Figure 7: Growth in Rents as a Function of Distance from the City Center

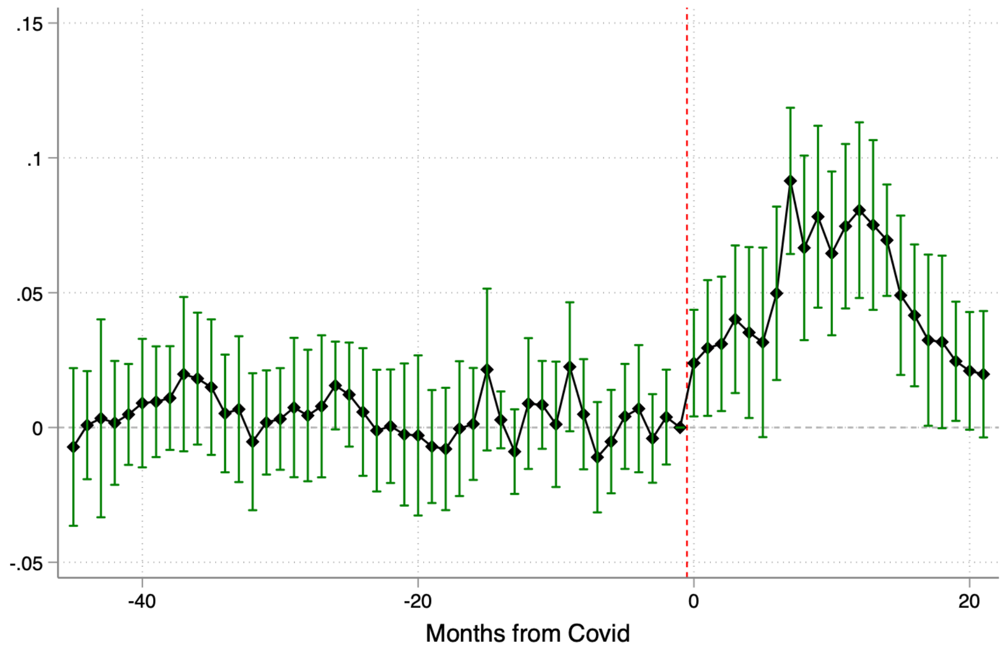


(a) Rents

(b) Rents (Placebo)

Notes: Each dot represents one of London's local authorities (e.g., Camden, Hackney). In panel (a), the x-axis plots the change in average rents between the year prior to COVID-19 and January to December 2021. In the placebo specification (panel (b)), the x-axis plots changes in 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 rents and property size (in square meters) are excluded. A linear fitted line is added to each plot.

Figure 8: Month-Specific Distance Coefficients: Rents (London)



(a) 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 rents and size (in square meters) are excluded. 95% confidence intervals are shown in green.

Table 19: Impact of Distance to City Center on Rents: Robustness

	(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

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

Notes: 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.

E London population

(a) London Population

Notes: London Metropolitan Area Population. Source: United Nations World Urbanization Prospects report.