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Household Heterogeneity and Choices of Work and Consumption

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Declaration

I, Morgane Marie Richard, confirm that the work presented in my thesis is my own. Where information has been derived from other sources, I confirm that this has been indicated in the thesis.

Morgane Marie Richard
June 27, 2024

Abstract

This thesis consists of three chapters on household heterogeneity and choices of work and consumption.

Chapter 1 studies the impact of risk heterogeneity on durable consumption over the business cycle. I examine household risk heterogeneity through the lens of labour contract type, and document that during the Great Recession, fixed-term contract workers reduced their car purchases significantly more than their permanent counterparts. Using an incomplete market model of durable and non-durable consumption with a dual labour market, I show that households that experienced an increase in downside income risk (such as permanent contract holders) adopted a "wait-and-see" strategy for their durable purchases, while households that experienced a decline in upside income risk (such as fixed-term contract holders) adopted a "wait-to-downgrade" approach.

In Chapter 2, I study the impact of the recent rise in remote work on households' consumption, wealth and housing decisions, examining both short-run and long-run effects. Using a heterogeneous agent model with endogenous housing tenure and city geography, I show that remote work shifts households' housing demand by increasing the demand for space and reducing the commuting costs. It affects where people live in the city and their housing wealth accumulation. The effects vary by access to remote work, income, and wealth. The rise in work-from-home can be compared to a suburb-wide gentrification shock as wealthy telecommuters opt for larger suburban homes, displacing marginal owners who turn to renting. In the long-run, work-from-home leads to the rise of a *tele-premium*.

Chapter 3 provides novel empirical evidence on London house prices and rents. Using rich property-level data, I show that larger properties and properties located away from the city center appreciated the most since the rise in remote work. I estimate a hedonic pricing schedule and document a rise in the premium for space and a decline in the commuting penalty.

Impact Statement

This thesis studies housing and durable consumption, and how they interact with household heterogeneity. On the one hand, housing and durable purchases are subject to non-convex adjustment costs, which implies that their behaviour is very different from that of non-durable consumption. In response to shocks, housing and durables act as amplifying mechanisms that affect the distribution of household income, consumption and wealth. On the other hand, decisions to adjust housing and durables depend to a large extent on households' existing stock of these assets, but also on households' income and wealth. Therefore, there is an interesting double feedback mechanism between housing/durable consumption, and household heterogeneity. My research examines this double feedback mechanism and its implications for inequality.

Chapter 1 focuses on how risk heterogeneity - examined through the lens of the type of labour contract - affects households' durable and non-durable consumption patterns during the Great Recession. Identifying which households experience large consumption declines over the business cycle is key to determining the distributional impact of recessions. The model also provides a laboratory for analysing the impact of public policy. In this context, I show that a car purchase subsidy has a limited ability to stimulate consumption of households facing a decline in their upside income risk, and is *de facto* partly transformed into a downgrading subsidy.

Chapters 2 and 3 analyse how the recent rise in work-from-home has affected income, consumption, and wealth inequality through changes in housing demand. The shift to remote work is highly persistent. Exploring the implications of this phenomenon is therefore crucial to understanding the long-term challenges facing our economy. I show that remote work has a significant impact on household housing demand, urban structure and housing affordability - issues that are all highly relevant to policymakers. Again using my model to quantify the impact of public policy, I show that programmes to facilitate the conversion of commercial property into housing would significantly mitigate the negative distributional effects of remote working.

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Chapter 1

Durable Consumption during the Great Recession: the Role of Risk Heterogeneity

1.1 Introduction

Durable consumption is one of the main driver of business cycle volatility. Consequently understanding how it interacts with employment and income risk is key to studying amplification mechanisms in recessions. What is more, households are heterogeneous in the level, nature, and fluctuations of their income risk. This is true, for example, of workers in different sectors of the economy or different cohorts.

This paper presents novel empirical evidence and a new theoretical framework for examining the impact of risk heterogeneity on durable consumption over the business cycle. I study households' risk heterogeneity through the lens of type of labour contracts. In many European countries including Italy, France, Spain, Sweden, Norway, Denmark and Finland, the labour market is segmented between workers employed with permanent contracts (i.e. indefinitely) and workers employed with fixed-term/temporary contracts (i.e. for a short and predetermined period only). Given their differing levels, nature and fluctuations of income and employment risk, comparing these workers is a promising approach to understanding the impact of risk heterogeneity. I start with some empirical motivation on durable and non-durable consumption between 2002 and 2014. I then build a dynamic heterogeneous agent model with durable and non-durable consumption where durable purchases are subject to a friction and the labour market is segmented into two types of contract.

Models studying durables over the business cycle focus on *ex-post* heterogeneity only (i.e.wealth heterogeneity resulting from transitory income shocks). Alternatively, in my framework, the type of contract represents a form of very persistent risk that lies between *full ex-ante* heterogeneity and the *ex-post only* heterogeneity of existing models. To the best of my knowledge, the impact of this more persistent heterogeneity has not been previously investigated. Furthermore, I analyse the extensive and intensive margins of durable consumption separately. The extensive margin of durable consumption corresponds to the share of households who purchase durable goods in a given period. The intensive margin is the amount spent on durable goods, conditional on purchasing them. I show that risk heterogeneity manifests differently across both adjustment margins.[1] This addresses a gap in the literature, which has mostly focused on the extensive margin of durable consumption.

There are three main findings. First, the increase in downside income risk is driving permanent contract workers' car response over the Great Recession. They adopt a "wait-and-see" strategy. Conversely, the decline in upside income risk is driving fixed-term contract workers' car response over the same period. They adopt a "wait-to-downgrade" approach. Second, around 40% of fixed-term contract workers' drop in car consumption is explained by a composition effect. The omission of this composition effect would result in a significant overestimation of the non-convex adjustment cost of cars. Third, a durable goods subsidy has limited ability to to stimulate durable consumption among

[1]This is in line with Bertola, Guiso and Pistaferri (2005), who show that the two margins of durable consumption are driven by different economic factors.

households experiencing a decline in upside income risk. The policy will, *de facto*, be partly transformed into a *downgarding subsidy*.

To conduct the empirical analysis I use data from the Survey of Households Income and Wealth (SHIW), conducted by the Bank of Italy. The SHIW dataset is notable for its comprehensive coverage of demographic and job-related characteristics, as well as detailed information on households' income, wealth, durable good expenditures, and non-durable consumption. Car purchases are used to measure households' durable consumption and I compare households whose members are employed with permanent contracts (referred to as permanent households for convenience) and households whose members are employed with fixed-term or temporary contracts (referred to as fixed-term households). The results highlight a stark and unevenly distributed drop in car purchases over the Great Recession. First, consistent with the findings of Attanasio et al. (2022), households sharply reduce their car purchases across both adjustment margins. Second, and this is a novel finding from this paper, the drop in car consumption is significantly larger for fixed-term households. During the Great Recession, the share of fixed-term households buying a car in a given year dropped by more than 40%, twice as much as for permanent households. On the intensive margin, fixed-term households reduced their spending by 17% compared to 12% for their permanent counterparts.

I then build and calibrate a model of household consumption and saving behaviour. The model is an incomplete market model in which households consume durable and non-durable goods. Durable purchases are subject to a non-convex adjustment cost *a la* Grossman and Laroque (1990). Following the empirical specification, I model two types of contract, each associated with a particular unemployment risk and income process. The policy functions derived from the model show that households update their durables according to a trigger-target (S,s) rule.[2] As durable investments are partially irreversible,

[2](S,s) dynamics are studied by Attanasio (2000), Bar Ilan and Blinder (1992), Bertola et al. (2005), Caballero (1993), Caballero and Engel (1999), Eberly (1994) and Foote et al. (2000), among others.

households wish to limit the frequency of such purchases. This result is consistent with the empirical literature documenting lumpy durable consumption patterns.

I solve for the model's policy functions by implementing the NEGM+ algorithm developed in Druedahl (2021). This algorithm extends the endogenous grid-point method of Carroll (2006) to an economy with non-convexity and exploits the nested structure of the problem. The rich income and risk processes associated with each contract-type are estimated using the SHIW data. I then parameterize the model to be consistent with key features of the Italian economy between 2002 and 2006. Using the model, I simulate households' consumption response to a shock calibrated to replicate the Great Recession. Crucially, the model succeeds in matching the durable consumption patterns observed in the Great Recession along both adjustment margins for permanent and fixed-term households.

I then disentangle the impact of the change in households' risk from that of realised income losses in explaining the durable consumption contraction observed during the recession. To do this, I compare the baseline Great Recession experiment to a placebo in which households believe they are in a recession, but the underlying shocks hitting the economy are expansionary. The impact of risk is heterogeneous across contract types. For permanent households, change in risk explains half of the baseline decline in the extensive margin of car purchases but none of the decline in the intensive margin. The change in permanent households' risk profile during the Great Recession shifts down their trigger adjustment point (s), without impacting their optimal durables stock (S). For fixed-term households, change in risk accounts for about one-third of their baseline decline in cars extensive margin and 10% of their decline in cars intensive margin. Change in risk pushes down both their adjustment trigger (s) and their optimal durables stock (S). This heterogeneity is explained by the different nature of the risk faced by permanent and fixed-term contracts.

The increase in downside income risk is driving permanent households' car response over the Great Recession. The associated strategy is "wait-and-see". The income distribution of permanent households is negatively skewed. During the Great Recession, their probability of falling into unemployment or being downgraded to a fixed-term contract rises, increasing the variance and negative skewness of their income distribution. Since durables have non-convex adjustment costs, buying a car is a commitment that permanent households are less willing to make in an environment of high downside income risk. In such times, it is optimal for them to delay the purchase of durables and wait for uncertainty to subside.[3] This "wait-and-see" strategy triggers a sharp but short-lived decline in the extensive margin of car purchases.

The decline in upside income risk is driving fixed-term households' car response over the Great Recession. The associated strategy is "wait to downgrade". Unlike their permanent counterparts, fixed-term households' income distribution is positively skewed. This is because, for them, the main source of large income changes is being upgraded to a permanent contract. Fixed-term households have a lot of room to move up. However, during the Great Recession this upgrade probability falls significantly, leading to a 30% reduction in their income variance. Upside income risk has collapsed. As a result, households would like to reduce their stock of durable goods, but the non-convex adjustment cost makes selling cars extremely costly. As depreciation naturally reduces the value of cars over time, fixed-term households use this mechanism to downsize and save on transaction costs. In essence, they "wait-to-downgrade". Depreciation is a slow process, therefore fixed-term households' "wait-to-downgrade" strategy is persistent and continues throughout the recession.

Focusing on realised resource losses, I assess the importance of the composition effect. To be considered a permanent (fixed-term) worker, one must have been employed with a permanent (fixed-term) contract for at least 6 months in the year. Consequently, a proportion of households in the permanent (fixed-term) group will have experienced some spells of unemployment or fixed-term

[3] In line with Bernanke, (1983) and Dixit and Pindyck (1994).

(permanent) contract during the period of interest. The number of households experiencing these alternative employment statuses depends on the aggregate state of the economy. Given the persistence of permanent contracts, the composition effect does not explain their car consumption patterns. Conversely, the composition effect accounts for around 40% of the decline in car purchases by fixed-term households along both adjustment margins. This is because, in recessions, these households are more likely to have experienced spells of unemployment and significantly less likely to access a permanent contract. If the researcher were to ignore the composition effect and tried to match the cars extensive margin of fixed-term households during the Great Recession, the non-convex adjustment costs would be estimated to be around 35%.

Finally, I use the model as a laboratory and examine the impact of a car subsidy equivalent to a payment of 5% of car expenditures in 2009. The results indicate the car subsidy merely induces households to front-load their car investments, leading to depressed car consumption in the post-program period. It also fails to stimulate the intensive margin of car consumption. Moreover, if the subsidy is targeted at households that have experienced a decline in upside income risk, it has even less ammunition to induce upward adjustment and may even be used by households to downsize their car. The policy is partly transformed into a *downgarding subsidy*.

This paper is related to the literature that studies lumpy durable consumption in macro models. Harmenberg and Oberg (2021) estimate the consumption response to an adverse labour market shock. Berger and Vavra (2015) show that non-convex adjustment frictions generate state-dependent responses to policy shocks, while McKay and Wieland (2021) highlight the inter-temporal trade-off for monetary policy in stabilising durables demand. Compared to these papers, my work focuses on risk heterogeneity (by modelling a dual labour market) and separates the intensive and the extensive margins of durable consumption. In this respect, this paper is related to Attanasio et al. (2022), who are the first to study both adjustment margins in the context of a life-cycle model. They use the CEX to derive cohort and business cycle decomposition of durable and non-durable consumption profiles. More broadly, this work relates to the study of income and consumption dynamics (see, for example, Blundell and Preston (1998), Guvenen et al. (2014) and Guvenen et al. (2021)) and the impact of uncertainty on household and firm decisions (see Bayer et al. (2019), Bloom (2009), Bloom et al. (2018) or Storesletten, Telmer and Yaron (2004), among others).

The remainder of the paper is structured as follows. Section 1.2 presents motivational empirical evidence. Section 1.3 presents the model. Section 1.4 describes the calibration, numerical implementation and policy functions. The Great Recession experiment and the relative importance of the change in risk and the composition effect are presented in Section 1.5. Finally, Section 1.6 investigates the impact of a car subsidy policy. Section 1.7 concludes.

1.2 Motivating Evidence

To study the impact of risk heterogeneity over the business cycle, this paper focuses on labour contracts in Italy. The Italian labour market is segmented into those with permanent contracts and those with fixed-term/temporary contracts, who face different income and risk fluctuations.

I use data from the Survey on Households Income and Wealth (SHIW) conducted by the Bank of Italy. The main strength of the SHIW dataset is that, alongside many demographic and job related characteristics, it provides detailed information on households' income, wealth, durable goods expenditures and non-durable consumption. I use the SHIW waves between 2000 and 2014 to compare changes in employment status, income and consumption between workers employed with permanent contracts and those with fixed-term or temporary contracts. When variables are reported at the household level (e.g. consumption), I compare households whose members are employed with permanent contracts (called permanent households for convenience) and households whose members are employed with fixed-term or temporary contracts (called fixed-term households). The frequency of the data is biannual. A further presentation of the dataset, details on variables definition and sample selection, as well as summary statistics may be found in Appendix A.

Table 1.1 displays each group's changes in income, non-durable consumption and detailed car purchases over the Great Recession. The Great Recession refers to the 2008-2014 period (i.e. the 2008-2009 recession as well as the recessionary episode of 2011-2013 sometimes referred to as the sovereign debt crisis). One aim of this paper is to study the extensive and the extensive margin of durable consumption separately. Studying changes in the intensive margin on a basket of goods is misleading.[4] Therefore, I restrict the durables to a single good: cars. I choose this particular item as - abstracting from houses as is done in this paper - cars represent the largest durable good purchased by households (between 2002 and 2014 cars alone accounted for roughly 30% of all durable purchases). In the remainder of the paper, I use cars and durables interchangeably.

Table 1.1. Consumption and Income Response to the Great Recession

	Cars ext. margin (€)		**Cars int. margin (€)**		**Non-dur. cons. (€)**		**Income (€)**	
	Perm.	F.t.	Perm.	F.t.	Perm.	F.t.	Perm.	F.t.
Boom	15.76	12.53	6,869	5,458	15,549	11,180	32,012	17,199
Recession	12.42	6.96	6,026	4,507	15,192	11,175	29,976	15,418
Change	**-0.21**	**-0.44**	**-0.12**	**-0.17**	**-0.02**	**0.00**	**-0.06**	**-0.10**

Notes: Perm. stands for permanent contract and F.t. for fixed-term or temporary contract. Boom is 2002-2006, Recession is 2008-2014. Non-dur. cons. stands for non-durable consumption, ext. for extensive and int. for intensive. Income is income from labour and transfers. Top and bottom 1% are winsorised. Households sampling weights are used.

Table 1.1 highlights a stark and unevenly distributed drop in car purchases over the Great Recession. First, in line with the findings of Attanasio et al. (2022), households strongly decreased their car purchases across both adjustment margins. Second, and this is a novel finding from this paper, the car

[4] If agents buy a car in a given year and a sofa in the following year, it does not mean that they decreased their intensive margin of durable consumption. The drop in the value of the purchases is simply a reflection of different types of investment.

consumption drop is significantly larger for fixed-term households. Over the Great Recession, the share of fixed-term households buying a car in a given year dropped by more than 40%, twice as much as for permanent households. On the intensive margin, fixed-term households reduced their expenses by 17% compared to 12% for their permanent counterparts. Finally, both groups more or less maintained their non-durable purchases over the recession. This holds despite a drop in mean income from labour and transfers of 6% and 10% for permanent and fixed-term households respectively.

Beyond income and consumption patterns, different types of contract also face heterogeneous levels and fluctuations of employment risk. Table 1.2 shows workers' employment status transition probabilities before and during the Great Recession. In the expansionary period, workers employed with fixed-term contracts had a 49% probability to be employed with a permanent contract in the next wave of the survey (i.e. two years later) and a 15% probability to become unemployed at the same time horizon. During the Great Recession, the two-year horizon probability to upgrade to a permanent contract dropped to 33%, while the unemployment risk increased to 20%. These workers record a significant drop in their upside employment risk and a rise in their downside employment risk. Permanent contract holders cannot upgrade to a more stable contract type, but they can either downgrade to a fixed-term contract or become unemployed. At a two-year time horizon, these events occurred with a probability of 4% and 3% in boom, and 6% and 5% in recession. As a result, the downside employment risk for permanent workers increased during the Great Recession.

Table 1.2. Probability to Change Employment Status (Two-year Horizon)

	Up. to perm.		**Down. to f.t.**		**Down. to u.**	
	Perm.	F.t.	Perm.	F.t.	Perm.	F.t.
Boom	-	0.49	0.04	-	0.03	0.15
Recession	-	0.33	0.06	-	0.05	0.20

Notes: Perm. stands for permanent contract, F.t. for fixed-term or temporary contract, and u. for unemployed. Up. stands for upgrade and Down. for downgrade. Boom is 2002-2006 and Recession is 2008-2014.

1.3 The Model

I formulate a model of household consumption and saving behaviour in which the labour market is segmented into two types of contracts, each associated with a particular unemployment risk and income process. The model is an incomplete market model where households consume durable and non-durable goods. Durable purchases are subject to a market friction. This specification is close to Berger and Vavra (2015) or Harmenberg and Oberg (2021).

1.3.1 The Household Problem

The economy is populated by a continuum of *ex-ante* identical households of measure one indexed by $i \in [0,1]$. Households are infinitely lived, time is discrete and a period is a quarter. They supply labour inelastically.

Preferences

Households derive utility from their non-durable consumption (c_t) and their stock of durable goods (D_t). They discount the future at rate β. The value function of household i can be written as:

$$V_i = E_0 \max_{\{c_{it}, D_{it}\}} \sum_{t=0}^{\infty} \beta^t u(c_{it}, D_{it})$$

$$with \quad u(c_{it}, D_{it}) = \frac{\left[c_{it}^{\alpha} D_{it}^{(1-\alpha)}\right]^{(1-\sigma)}}{1-\sigma}$$

where α is the weight of non-durable consumption in the utility function and σ is the coefficient of relative risk aversion.[5]

Idiosyncratic risk - employment risk

Households face an idiosyncratic employment risk. In a given period, a household can be either employed with a permanent contract, employed with a fixed-term contract or unemployed. Households with fixed-term contracts face a larger risk of becoming unemployed than households holding permanent contracts. Transitions between the three employment states follow a Markov process.

Idiosyncratic risk - income risk

Households also face a degree of labour income risk when they are employed. The logarithm of income follows an autoregressive process of order one given by:

$$log(y_{it}) = \mu + \rho log(y_{it-1}) + \xi_{it}$$

$$with \quad \xi_{it} \sim \mathcal{N}(0, \sigma_\xi^2)$$

where μ, ρ and σ_ξ^2 are the intercept, persistence and variance of the household's income process.

When unemployed, households receive unemployment benefit ($y_{it} = ub$) with probability p_{ub}. Alternatively, they receive a minor subsistence allowance ($y_{it} = sub$) with probability $1 - p_{ub}$.

Aggregate risk - employment transition

In addition to households' idiosyncratic income and employment risk, the economy is either in good aggregate state (called boom) or in bad aggregate state (called recession). These aggregate states are characterised by two distinct

[5]The evidence in Piazzesi and Schneider (2007) and in Ogaki and Reinhart (1998) motivates the choice of the Cobb-Douglas utility function.

matrices governing transitions between permanent employment, fixed-term employment and unemployment, as well as different levels of unemployment benefit.

Aggregate risk - wealth shocks

Asset markets are incomplete and households may self-insure against employment and income risk by saving in a composite asset a_t. The composite asset is made of securities valued at price q_t^s, real estate valued at price q_t^h, and some risk-free asset (deposit and valuables) valued at price 1.

Securities price is subject to some aggregate fluctuations following:

$$log(q_t^s) = \rho log(q_{t-1}^s) + \xi_{it}^s$$

$$with \quad \xi_{it}^s \sim \mathcal{N}(0, \sigma_{\xi^s}^2)$$

where ρ and $\sigma_{\xi^s}^2$ are persistence and variance parameters.

Similarly, real estate price is subject to some aggregate fluctuations following:

$$log(q_t^h) = \rho log(q_{t-1}^h) + \xi_{it}^h$$

$$with \quad \xi_{it}^h \sim \mathcal{N}(0, \sigma_{\xi^h}^2)$$

where ρ and $\sigma_{\xi^h}^2$ are persistence and variance parameters. I assume that securities and real estate price processes are independent.

Finally, the composite asset is bought and sold each period at price q_{jt}

$$q_{jt} = \omega_j^s * q_t^s + \omega_j^h * q_t^h + (1 - \omega_j^s - \omega_j^h) * 1$$

where ω_j^s and ω_j^h are the weights of securities and real estate in the households' portfolio. I assume that these weights are exogenous and depend on households' employment status j. Borrowing is not allowed in this economy.

Durable goods

Households may also self-insure by accumulating durable goods sold at price p. Durables stock D_t cannot be negative and depreciates at rate δ. Moreover, durable purchases are subject to a friction. When households decide to adjust their stock of durables, they have to pay a non-convex adjustment cost τ, which is proportional to the stock of durable goods held by the household before adjusting. This adjustment cost follows the specification of Grossman and Laroque (1990) and ensures to reproduce the lumpy patterns of durable consumption documented in the microdata.

Budget constraints

The budget constraint of a household deciding not to adjust their stock of durables is:

$$a_{it}q_{jt} + c_{it} \leq (1+r)q_{jt}a_{it-1} + y_{it}$$

where r is the interest rate on the composite asset.

Conversely, the budget constraint of a household deciding to adjust their stock of durables is:

$$a_{it}q_{jt} + c_{it} + pD_{it} \leq (1+r)q_{jt}a_{it-1} + y_{it} + (1-\tau)(1-\delta)pD_{it-1}$$

1.3.2 Recursive Formulation of the Problem

V is the value function of a household. For concision, the i subscripts are dropped.

$$V(m,D,y,j;\Omega) = max\{V^{keep}(m,D,y,j;\Omega), V^{adj}(x,y,j;\Omega)\}$$

$$s.t \quad x = m + (1-\tau)(1-\delta)pD$$

Where V^{keep} is the value function of a household who does not adjust durables and V^{adj} is the value function of a household who adjusts durables. m is the household's cash-in-hand and x is the cash-in-hand available to the household after having sold their beginning-of-period stock of durables D. y is income, j is the employment status of the household, and Ω is the vector of aggregate states of the economy (boom or recession for employment risk, price of securities q^s, and price of real estate q^h).

The keeper's problem is:

$$V^{keep}(m,D,y,j;\Omega) = \max_{a,c} U(c,D') + \beta E\left[V(m',D',y',j';\Omega')\right]$$

$$s.t \quad qa = m - c$$

$$D' = (1-\delta)D$$

$$m' = (1+r)q'a + y'$$

$$q = \omega_j^s q^s + \omega_j^h q^h + (1 - \omega_j^s - \omega_j^h)$$

$$q' = \omega_{j'}^s q^{s\prime} + \omega_{j'}^h q^{h\prime} + (1 - \omega_{j'}^s - \omega_{j'}^h)$$

$$y' \sim \Upsilon(y)$$

$$j' \sim \Phi(j)$$

$$\Omega' \sim \Gamma(\Omega)$$

where Υ is the conditional distribution of the idiosyncratic labour income, Φ is the conditional distribution of the employment status, and Γ is the conditional distribution of the aggregate states.

The adjuster's problem is:

$$V^{adj}(x,y,j;\Omega) = \max_{a,c,D'} U(c,D') + \beta E\left[V(m',D',y',j';\Omega')\right]$$

$$s.t \quad qa = x - c - pD'$$

$$m' = (1+r)q'a + y'$$

$$q = \omega_j^s q^s + \omega_j^h q^h + (1 - \omega_j^s - \omega_j^h)$$

$$q' = \omega_{j'}^s q^{s\prime} + \omega_{j'}^h q^{h\prime} + (1 - \omega_{j'}^s - \omega_{j'}^h)$$

$$y' \sim \Upsilon(y)$$

$$j' \sim \Phi(j)$$

$$\Omega' \sim \Gamma(\Omega)$$

Following the nested structure in Druedhal (2021), the adjuster's problem can be viewed as a sequential problem. The household first chooses how much durable goods to buy or sell, and then chooses non-durable consumption. I rewrite the adjuster's problem as:

$$V^{adj}(x, y, j; \Omega) = \max_{D'} V^{keep}(m, D, y, j; \Omega)$$

$$s.t \quad D' = (1-\delta)D$$

$$m = x - pD'$$

1.4 Parameterization, Numerical Implementation and Policy Functions

1.4.1 Parameterization

I parameterize the model to be consistent with key features of the Italian economy before the Great Recession (2002-2006). One period in the model is a quarter. I use a mixed parameterization strategy. A subset of parameters is fixed using standard values and the literature. Another set of parameters is calibrated to match moments from the Italian economy outside the model. The remaining parameters are jointly calibrated using the method of simulated moments inside the model. The parameter values are summarized in Table 1.3.

Table 1.4 shows the targeted moments.

Calibration of the employment risk

Quarterly employment risk is externally calibrated to match bi-annual transitions from the SHIW data. As mentioned above, households' transitions between the three employment states - employed with a permanent contract, employed with a fixed-term contract, and unemployed - are governed by two Markov processes: one in boom and one in recession. As type of contract is only available from 2000 in the data, I do not have access to an appropriate recession period before the Great Recession. Consequently, I use the SHIW data before 2008 to calibrate the model's quarterly transitions in boom, and the SHIW data between 2008 and 2014 to recover the model's transitions in recession. I use the method of matching simulated moments.[6] Appendix B.1 shows the bi-annual employment transitions from the data and the model. The quarterly transition matrices obtained using this procedure are reported below. Rows represent employment state today and columns employment state next period. p stands for employed with a permanent contract, $f.t$ employed with a fixed-term contact and u unemployed.

$$\mathbf{P_{boom}} = \begin{array}{c} \\ p \\ f.t \\ u \end{array} \begin{array}{c} \begin{array}{ccc} p & f.t & u \end{array} \\ \begin{pmatrix} 0.988 & 0.008 & 0.004 \\ 0.104 & 0.858 & 0.038 \\ 0.029 & 0.042 & 0.929 \end{pmatrix} \end{array} \quad , \quad \mathbf{P_{recession}} = \begin{array}{c} \\ p \\ f.t \\ u \end{array} \begin{array}{c} \begin{array}{ccc} p & f.t & u \end{array} \\ \begin{pmatrix} 0.984 & 0.010 & 0.006 \\ 0.063 & 0.894 & 0.042 \\ 0.019 & 0.030 & 0.951 \end{pmatrix} \end{array}$$

In a given aggregate state, permanent contract holders face a significantly lower risk of losing their job than fixed-term contract workers. Unemployed workers have higher chances to find fixed-term contracts than permanent ones

[6] I use the diagonal matrix of inverses of the moments' relative variances as a weighting matrix. Moments' variances are obtained with a thousand-repetition bootstrapping procedure.

to exit unemployment. Comparing aggregate states, employed workers (with any type of contract) have higher risk of falling into unemployment in recession. Similarly, it is harder for unemployed workers to transition back into employment in recession than in boom. Finally, moving from a fixed-term contract to permanent employment is significantly less likely when the economy is in recession.

Calibration of the income processes

Income processes are calibrated using the SHIW data between 2000 and 2006. In period t, the logarithm of household i 's income $log(y_{it})$ is given by:

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

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

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

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

where Z_{it} is a set of household's observable characteristics including type of contract and other demographic variables. Income residual $\tilde{y_{it}}$ has a persistent component P_{it} which follows an auto-regressive process of order one, and some i.i.d measurement error ϵ_{it}. Income residuals are obtained by performing a standard OLS regression of the logarithm of individuals' labour income on year dummies, type of contract, gender, age, age squared, education, region, and size of city. I then use variance covariance identifying restrictions to recover the persistent component's intercept, persistence and variance parameters. After discarding measurement error, the income process has a quarterly persistence a little above 0.98 and a variance of 0.0034. These estimates are in line with the boom quarterly values of Storesletten et al. (2004). Ultimately, type of contract specific average fitted values from the regression are added to the residuals to obtain the final grids of income for permanent and fixed-term workers. Values are normalised by the average quarterly income of permanent contract workers. Additional details are reported in Appendix B.2.

Unemployment benefit levels are set to reproduce mean unemployment transfers of households who do receive unemployment benefit. For boom, I take the SHIW data between 2002 and 2006. For recession, I consider observations between 2008 and 2014. The probability of receiving unemployment benefit is chosen to match the period's SHIW unemployment benefit coverage rate of roughly 12%.

Calibration of the wealth shocks

Securities price fluctuations are calibrated using the log of S&P500 adjusted close prices deflated by CPI between January 1985 and December 2007. After removing a linear trend, I use a standard OLS regression to recover the AR(1) persistence parameter and the variance of the residuals. A similar procedure is applied for real estate price fluctuations using the log of the real residential property price index for Italy between January 1980 and December 2007. Weights of securities and real estate in households' portfolio come from the SHIW data between 2002 and 2006. Permanent households' average portfolio consists of 5% of securities (including government bonds), 59% of real estate, and 36% of deposits and other real assets. Households do not hold any business assets as I excluded self-employed from the sample. Fixed-term households' portfolio consists of only 1% of securities (including government bonds), 46% of real estate, and 52% of deposits and other real assets. Unemployed households' portfolio weights are assumed to be the same as fixed-term households'.

Other parameters fixed outside the model

I set the coefficient of relative risk aversion to 2. The interest rate on the composite asset is set to .01, which delivers an annual interest rate of approximately 4%. Price of durable goods is normalised to 1. In line with Harmenberg and

Oberg (2021) and Attanasio et. al. (2022), I set car net depreciation to 10% per year. The subsistence allowance given to households who do not receive unemployment benefit is set to 0.06 (corresponding to €100 per month). Finally, I set the transitions between booms and recessions to match the average length of recessions (7.5 periods) and the share of total time spent in recessions (43%) in Italy between 1960 and 2016.[7] I use the OECD based recession indicators for Italy computed by the Fed of Saint Louis.

Table 1.3. Parameters

Parameter	Value	Description	Target
Households			
β	0.979	Discount factor	See Table 4
σ	2.00	Relative risk aversion	Standard value
r	0.01	Interest rate	Annual interest rate of 4%
α	0.934	Weight of n.d.c. in utility	See Table 4
τ	0.065	Dur. adjustment cost	See Table 4
δ	0.025	Depreciation rate	Annual depreciation of 10%
p	1.00	Dur. price	Normalisation
ub_{boom}	0.32	U.b in boom	Mean u.b 2002-2006
$ub_{recession}$	0.25	U.b in recession	Mean u.b 2008-2014
sub	0.06	Subsistence allowance	€100 per month
p_{ub}	0.12	Probability to get u.b	u.b coverage rate 2002-2014
Agg. state			
ρ_{bb}	0.90	Boom to boom transition	Time spent in rec.
ρ_{rr}	0.87	Rec. to rec. transition	Average length of rec.

Notes: All values are reported at the quarterly frequency of the model. N.d.c. stands for non-durable consumption, Dur. stands for durables, u.b stands for unemployment benefit, Rec. stands for recession.

Parameters jointly calibrated inside the model

I jointly calibrate the remaining parameters inside the model using the method of simulated moments on the SHIW data between 2002 and 2006.[8] Because

[7] Following the method in Krueger, Mitman and Perri (2016).

[8] As for the income process, I use a bootstrapping procedure with a thousand repetitions to get the moments' variances. I then take the diagonal matrix of inverses of the moments' relative variances as a weighting matrix.

of the non-convex adjustment cost, the model's wealth and durables stock are strongly path dependent. Consequently, extra care should be taken when setting up the initial condition in the simulations. Starting from the stationary distribution for durables and wealth, I simulate the model for the 1980-2001 period feeding in the path of realised aggregate shocks for Italy (OECD based recession indicators). I then compute the model's moments in the expansion period between 2002 and 2006. This procedure ensures that the moments from the model are comparable with their data counterparts. The jointly calibrated parameters are households' discount factor (β), cars non-convex adjustment cost (τ), and the weight of non-durables in the utility function (α). The set of targets and the associated estimates are displayed in Tables 1.3 and 1.4. The calibration results are well in line with estimates from the literature.

Table 1.4. Targeted Moments

Target	Model	Data	Source
Share of hh. buying a car in a year	0.16	0.16	SHIW 02-06
Mean car expenses norm. by income	0.33	0.33	SHIW 02-06
Median wealth norm. by income	3.55	3.55	SHIW 02-06

Notes: Hh. stands for households and Norm. stands for normalised. Income refers to yearly income from labour and transfers. The mean of car expenses is conditional on buying a car.

1.4.2 Model Fit: Non-targeted Moments

This subsection presents how the model fits some important moments that were not explicitly targeted in the calibration. Table 1.5 displays these cross-sectional moments in the model, and in the data. The data corresponds to years between 2002 and 2006. The model simulates the same time period, with the procedure to set up the initial condition explained in the previous subsection.

As shown on the top half of Table 1.5, the model is particularly successful in reproducing non targeted moments by type of contract. This is key as the aim of the paper is to analyse and compare permanent and fixed-term households' consumption patterns over the Great Recession. The model reproduces the share of permanent and fixed-term households who adjust their car, as well as ratios of car purchases, income and consumption by type of contract. The detailed calibration of contract specific income and employment risk and of cars adjustment cost explains why these non-targeted income and consumption moments are well aligned with the data. As is common in this type of models, I do not capture the high degree of wealth concentration among the very rich. Consequently the model underestimates permanent households' wealth relative to that of fixed-term households.

The bottom part of Table 1.5 displays moments for the entire population. The model matches each of these non-targeted moments closely with the exception of car purchases' cross-sectional standard deviation. This was expected as, in the solution method, households choose car purchases on grid-points. The variance of such expenses is therefore underestimated.

1.4.3 Numerical Implementation

I solve for the model's policy functions in partial equilibrium by implementing the NEGM+ algorithm developed in Druedahl (2021). This algorithm extends the endogenous grid-point method of Carroll (2006) to an economy with non-convexity and exploits the nested structure of the problem. An additional layer of optimisation is attained with an enhanced interpolation method. I solve for households' policies on a 30-point grid for durables stock, and 200-point grids for regular cash-in-hand, cash-in-hand after reselling the stock of durables, and liquid assets. As there are three grids to represent the same dimension (cash-in-hand, cash-in-hand after reselling the stock of durables, and liquid assets), particular care should be taken in setting up these three grids relatively to each other. The top of the grid for cash-in-hand after selling the stock of durables should be larger than that of the assets grid. This is the case as households should use some of their resources for consumption. Moreover, setting the maximum level of cash-in-hand after selling durables equal to the sum of the tops

Table 1.5. Non-targeted Moments

Moment	Model	Data
By type of contract		
Share of car adjusters - perm.	0.17	0.16
Share of car adjusters - f.t.	0.13	0.13
Ratio perm./f.t. - car purchases	1.27	1.26
Ratio perm./f.t. - income	1.86	1.86
Ratio perm./f.t. - cons.	1.39	1.40
Ratio perm./f.t. - wealth	1.31	2.00
Overall population		
Mean ratio car purchases / cons.	0.32	0.43
Mean ratio car purchases / stock cars	0.73	0.73
Mean ratio stock cars / cons.	0.42	0.47
Mean share of cars in total assets	0.11	0.07
Share of car downgraders	0.005	0.006
Sd. of income	0.47	0.55
Sd. of car purchases	0.32	0.78
Sd. of cons.	0.34	0.45

Notes: Cons. stands for non-durable consumption. Ratio perm./f.t. refers to the mean of the variable for permanent households over the mean of the variable for fixed-term households. Sd. is the cros sectional standard deviation normalised by the mean. Income refers to income from labour and transfers. Car purchases are conditional on buying a car. Total assets refer to wealth + stock of cars.

of the cash-in-hand and durables stock grids ensures that the grid is wide enough for comparing the adjust and keep cases. The labour income autoregressive processes for permanent and fixed-term workers are each discretized into five states Markov processes using Rouwenhorst's method. In addition to the ten employment states, there also exists two unemployment states (unemployed households who receive unemployment benefit or not) bringing the number of idiosyncratic states to 12. The economy can be in boom or in recession (high or low employment risk). Additionally there are 9 aggregate states for wealth shocks as securities and real estate price processes are each discretized into three states Markov processes with Rouwenhorst method. I iterate the value function until convergence using the absolute value of the largest difference as an error metric and a tolerance level of 1e-3.

1.4.4 Decision Rules

Figure 1.1. Policy Function: Stock of Durables

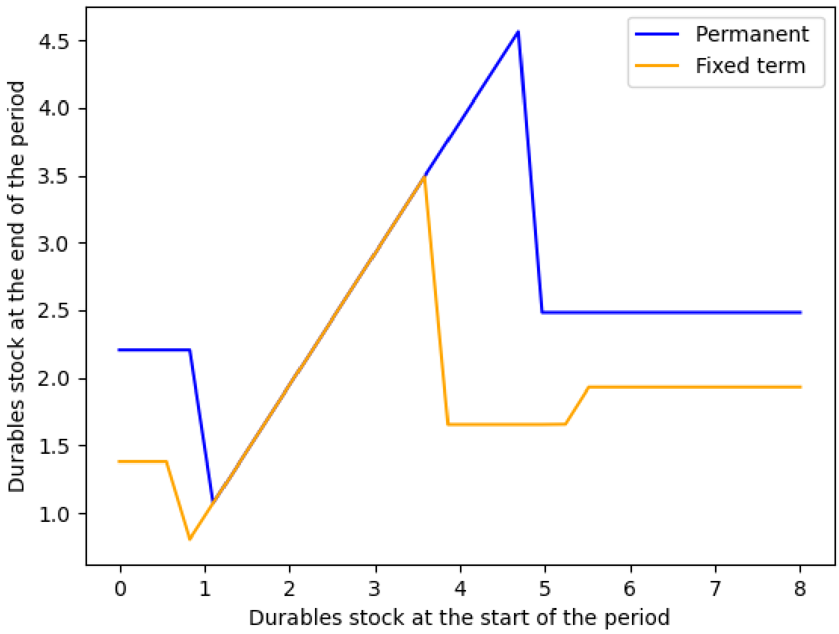
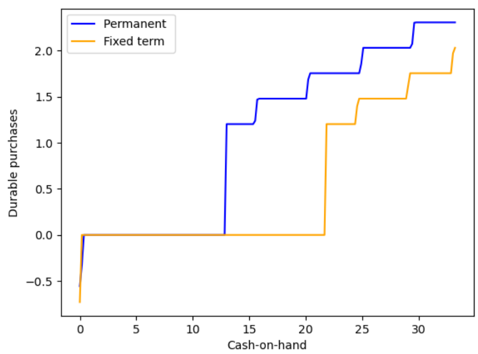
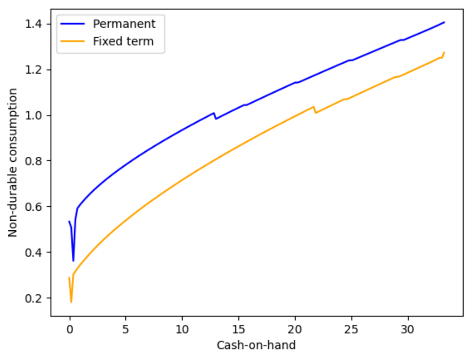


Figure 1.2. Policy Functions



(a) Durable Purchases



(b) Non-durable Consumption

Figure 1.1 plots choices of durables stock as a function of durables stock at the start of the period for permanent (in blue) and fixed-term households (in yellow).[9] These policy functions illustrate that households update their

[9]The other states are held fixed to mean cash-in-hand, mean income, boom aggregate

durables following trigger-target (S,s) rules. As durable investments are subject to a non-convex transaction cost, agents wish to limit the frequency of such adjustments. Households will decide on a minimum stock of durables under which they do not want to sink and a maximum stock of durables above which it is inefficient for them to go. As long as their durables stock is between these two bonds, they will not make any adjustment and simply let their durables depreciate. Once the stock of durables depreciated below the lower trigger point, households become willing to pay the adjustment cost to bring their durables up to a target value. Figure 1.1 shows adjustment trigger and target points for buying and selling durables. In between these points, households are in the inaction region.

Figure 1.1 also highlights the difference between permanent and fixed-term households. Permanent households' optimal stock of durables is higher than that of fixed-term households. Moreover, fixed-term households will wait longer before buying new durables and will sell their existing stock faster than their permanent counterparts. Fixed-term households' inaction region is shifted downwards. The discrepancy between the two types of contract's durable consumption is also illustrated in Panel a of Figure 1.2 where durable purchases are plotted against cash-in-hand.[10] Here, the inaction region of fixed-term households is larger than that of the permanent group as they will need a higher level of cash-in-hand to prompt an upward adjustment. Moreover, conditional on buying durables, the value of fixed-term households' purchases is lower than permanent households' tickets. For very low levels of cash-in-hand, durable purchases are negative. This is a region where households sell their current durables to afford non-durable consumption.

Finally, Panel b of Figure 1.2 plots non-durable consumption as a function of cash-in-hand.[11] As non-durable consumption isn't subject to frictions, there

state for employment risk, and median prices for securities and real estate.

[10]The other states are held fixed to mean stock of durables, mean income, boom aggregate state for employment risk, and median prices for securities and real estate.

[11]Once again the other states are held fixed to mean stock of durables, mean income, boom

are no inaction region or (S,s) type behaviours. The drop in consumption at the start of the x-axis corresponds to when households stop selling their existing durables to afford non-durable consumption. Similarly the downward step in consumption at higher levels of cash-in-hand indicates that some resources are shifted towards buying durable goods.

1.5 The Great Recession

1.5.1 The Great Recession - Baseline

I simulate the model's response to a shock calibrated to reproduce the Great Recession and study the durable and non-durable consumption patterns of permanent and fixed-term households. As in the calibration procedure, I take care when setting up the simulations' initial condition because durable purchases are path dependent. I start the simulations by feeding in realised booms and recessions between 1980 and 2001 using Italy's OECD based recession indicators. I then simulate a boom for the 2002 to 2007 period where securities price is held median and real estate price is high (to be consistent with the surge in real estate's value prior to the Great Recession). I then simulate the Great Recession from 2008 to 2014 with recession specific employment risk, low securities and real estate prices, as well as an additional MIT shock to labour income calibrated to reproduce the labour income drop experienced by fixed-term and permanent households during this period. The length of the episode and the extra income drop confer an exceptional nature to the Great Recession.

The aim of this exercise is to evaluate if the model is able to reproduce the empirical facts in the motivation section of the paper. Therefore, the data sample selection should be reproduced in the model simulations. In the data, households report their employment status for the majority of the year. Consequently, households who belong to the fixed-term (permanent) group could have been employed with a permanent (fixed-term) contract or unemployed for

aggregate state for employment risk, and median prices for securities and real estate.

a small time during the year. The same is true for the model simulations.

The results of the Great Recession experiment are reported in the first panel of Table 1.6 where the estimates from the motivation section (Table 1.1) are compared to their model counterparts. Each type of household's drop in labour income are targeted moments, while the changes in car and non-durable consumption are not targeted. The model is successful in reproducing the patterns observed during the Great Recession. Over the period, the model share of households purchasing a car dropped by 22% and 42% for permanent and fixed-term households, against 21% and 44% in the data. Moreover, fixed-term household's intensive margin of car purchases decreased by 19% in the model, compared to 17% in the data. These figures are 9% and 12% for permanent contract holders. Finally the model closely tracks the change in permanent households' non-durable consumption, while overestimating a little the contraction for fixed-term households.

Table 1.6. Great Recession Experiment

	Cars ext. margin		**Cars int. margin**		**Non-dur. cons.**		**Income**	
	Perm.	F.t.	Perm.	F.t.	Perm.	F.t.	Perm.	F.t.
Model vs. Data								
Model	-0.22	-0.42	-0.09	-0.19	-0.03	-0.05	-0.06	-0.10
Data	-0.21	-0.44	-0.12	-0.17	-0.02	0.00	-0.06	-0.10
Baseline vs. Placebo								
Baseline (model)	-0.22	-0.42	-0.09	-0.19	-0.03	-0.05	-0.06	-0.10
Placebo (model)	-0.10	-0.14	0.01	-0.02	0.00	0.00	0.0	0.01
Baseline vs. No Compo								
Baseline (model)	-0.22	-0.42	-0.09	-0.19	-0.03	-0.05	-0.06	-0.10
No compo. (model)	-0.21	-0.26	-0.09	-0.12	-0.03	-0.04	-0.06	-0.08

Notes: This table reports changes between boom (2002-2006) and the Great Recession (2008-2014) in the data and various model simulations. No compo. refers to the "no composition effect" experiment. Perm. stands for permanent contract and F.t. for fixed-term or temporary contract. Non-dur. cons. stands for non-durable consumption, ext. for extensive and int. for intensive. Income is income from labour and transfers. In the estimates from the data, top and bottom 1% are winsorised and households sampling weights are used.

1.5.2 The Role of Risk

The previous subsection established that the model is successful in reproducing the observed consumption patterns of permanent and fixed-term households over the Great Recession. I now want to disentangle the impact of the change in households' risk from that of realised income losses. To this end, I compare my baseline Great Recession experiment to a placebo experiment. In the placebo experiment, the households believe that they are in recession (they use their recession policy functions), but the underlying shocks hitting the economy are expansionary. More precisely, the aggregate state for employment risk is boom, securities and real estate prices are the same as during the 2002-2006 period, and there is no additional MIT labour income drop. The middle panel of Table 1.6 displays the model simulations for the baseline and the placebo experiments.

Unlike consumption and income, households' car purchases respond to the placebo scenario. Still, the nature of the response differs by type of contract. For permanent households, none of the baseline's cars intensive margin drop is accounted for by change in risk. Instead, the contraction in durables' intensive margin is only explained by realised income losses. Conversely, half of their baseline decline in the share of car buyers still takes place in the placebo experiment, implying that change in risk prompts permanent households to delay their durable purchases. Consequently, the change in permanent households' risk profile during the Great Recession shifts down their trigger adjustment point (s), without impacting their optimal durables stock (S). The story is different for fixed-term households as change in risk accounts for around a third of their baseline drop in cars extensive margin and for 10% of their drop in cars intensive margin. Change in risk shifts down fixed-term households' adjustment trigger (s) as well as their optimal durables stock (S).

The heterogeneity in the change of (S,s) rule's parameters across types of contract is explained by the heterogeneous nature and changes of the risk faced by the households. Table 1.7 displays moments of the income distribution in boom and during the Great Recession by type of contract.[12]

Table 1.7. Moments of Households' Income Distribution

	Mean		**Variance**		**Skewness**	
	Perm.	F.t.	Perm.	F.t.	Perm.	F.t.
Boom	1.035	0.544	0.011	0.049	-4.091	2.299
Recession	1.032	0.520	0.013	0.035	-4.402	2.430
Change	0.0	-0.04	0.24	-0.29	0.08	0.06

Notes: Perm. stands for permanent contract and F.t. for fixed-term or temporary contract. Boom is 2002-2006, Recession is 2008-2014. Income is income from labour and transfers.

Permanent households and downside income risk

First, we consider permanent households. Consistent with Guvenen et al. (2021), the income distribution is negatively skewed. Upon entering the Great Recession, permanent households see that their average income remains the same, their income variance rises by nearly a quarter, and their income distribution becomes more negatively skewed. This increase in variance and negative skewness is driven by the rise in the probability to fall into unemployment or to become a fixed-term worker. There is an expansion of the lower tail of the income distribution as permanent households see a rise in the risk of large income declines. This risk pattern interacts with car expenses as the non-convex adjustment cost makes car purchases partially irreversible. In other words, buying a car is a commitment that permanent households will be less willing to make in an environment with large downside income risk. In such times, it is optimal for them to delay durable purchases and wait until the uncertainty subsides. Higher income uncertainty encourages permanent households to "wait-and-see", widening the inactivity region of their policy function. The rise in downside income risk is driving permanent households' car response over the Great Recession. The associated strategy is "wait-and-see".

[12] These moments are computed without the MIT income drop.

Fixed-term households and upside income risk

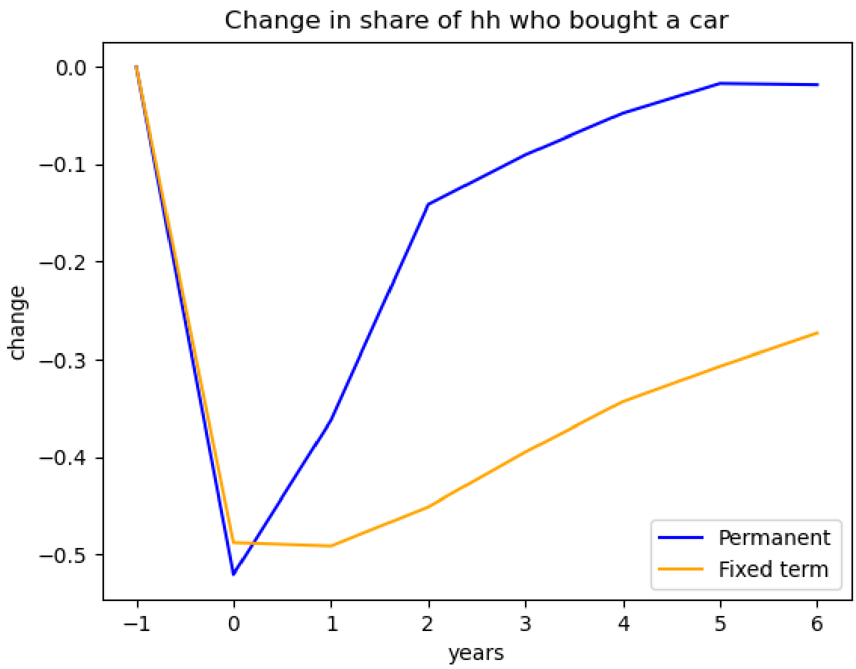
Interestingly, Table 1.7 shows that fixed-term households' income distribution is positively skewed. This is the case as, for them, the main source of large income changes is to be upgraded to a permanent contract. Fixed-term households have a lot of room to move up. Upside income risk is an important feature of their income process. Upon entering the Great Recession, fixed-term households face a 4% decline in their income mean alongside a 30% drop in income variance. Moreover their income distribution becomes less positively skewed. This is the case as the probability to get upgraded to a permanent contract reduces significantly (from 10.4% to 6.3% during the Great Recession). There is a compression of the upper tail of the income distribution.[13] In terms of durable consumption, the standard "wait-and-see" story is a poor description of fixed-term households' behaviour as they do not need to wait for the uncertainty to subside - it already has. Instead, households would like to downsize their stock of durables, but the non-convex adjustment cost makes selling cars extremely costly. Moreover because it is non-convex, the cost is particularly discouraging for low income low wealth households who are over represented amongst fixed-term contracts. As depreciation naturally reduces the value of cars over time, fixed-term households use this mechanism to downsize and save on transaction costs. In essence, they "wait-to-downgrade". The drop in upside income risk is driving fixed-term households' car response over the Great Recession. The associated strategy is "wait-to-downgrade".

Persistence of consumption contraction

Finally the driver of the drop in durable purchases - upside versus downside income risk - has a significant impact on the length of the contraction. Figure 1.3 plots changes in the extensive margin of car purchases for permanent households (in blue) and for fixed-term households (in yellow). The baseline period

[13] Fixed-term households also experience a small rise in unemployment risk during the recession. Still, the most important driving force is the decline in upside income risk as illustrated by the reduction in income variance and 90th percentile.

Figure 1.3. Persistence of "Wait-and-See" *versus* "Wait-to-Downgrade"



(t=-1 on the plot) is 2007, while the Great Recession starts in 2008 (t=0 on the plot) and lasts for the whole plotted period. On the one hand, for permanent households, the drop in the extensive margin of car purchases is relatively short-lived. As the recession draws longer, depreciation reduces the value of households' stock of cars. Eventually, this value sinks to such a low level that permanent households are forced into adjusting despite the ongoing recession. On the other hand, for fixed-term households, depreciation is a lengthy process. The "wait-to-downgrade" strategy is persistent and lasts throughout the recession.

1.5.3 The Composition Effect

Beyond change in risk, households also adjust their saving and consumption patterns because they experience resources loss during the Great Recession. These losses come from two channels: i) the "exogenous losses" (wealth shocks and MIT income drop) and ii) the composition effect. The composition effect refers to which households are selected in the permanent and fixed-term groups. To be considered a permanent (fixed-term) worker, one needs to have been employed with a permanent (fixed-term) contract for at least 6 months in the year. Consequently, a share of households in the permanent (fixed-term) group will have gone through some spells of unemployment or fixed-term (permanent) contract in the period of interest. How many households do go through these alternative employment states depends on the Markov matrix governing employment transitions, which is state dependent.

To quantify the relative importance of the two resources loss channels, I compare the baseline experiment to a "no composition effect" experiment. In the "no composition effect" experiment, I use the employment state transition matrix calibrated for the expansion time, even during the Great Recession. Households still believe that their employment risk has changed (they use their recession policy functions) and the exogenous income and wealth losses are as in the baseline. This experiment removes the composition effect: the employment states of the households selected in a given group are exactly the same as if the Great Recession did not occur.

The bottom panel of Table 1.6 displays the results of the "no composition effect" experiment for permanent and fixed-term households. First, permanent households' baseline and "no composition effect" experiments are similar, implying that composition effect does not play a role for these households. Given the persistence of the permanent contracts, there is only a residual share of the selected households who have gone through any other employment state during the year. This is true in boom and in recession. Therefore, the sole change in the realised transition matrix does not affect the households selected in the permanent group much.

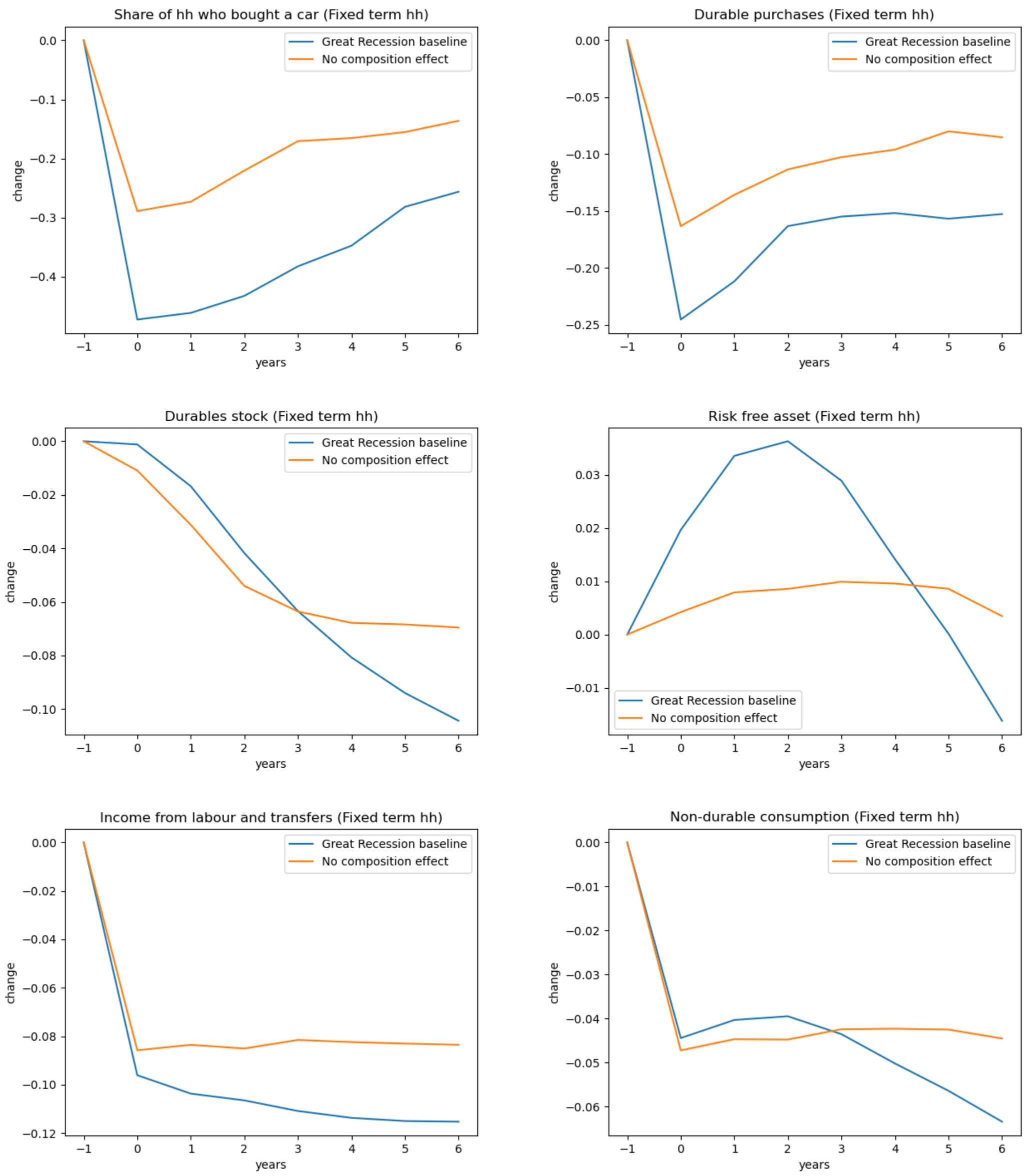
Conversely, the composition effect accounts for around 40% and 35% of fixed-term households' drop in car purchases extensive and intensive margins. It is the case as fixed-term contracts are significantly less persistent than permanent ones. Therefore, households selected in the fixed-term group are much more likely to have gone through other employment states over the period. In recession they are more likely to have gone through unemployment spells and significantly less likely to access a permanent contract.[14] If the researcher were to omit the composition effect and attempt to match fixed-term contracts' car purchases extensive margin over the Great Recession, the car non-convex adjustment cost would be highly overestimated. For instance, one would need a non-convex adjustment cost of 35% (against 6.5% estimated in the paper) to obtain a close to 40% drop in fixed-term households' cars extensive margin. Such an adjustment cost is unreasonable.

Figure 1.4 provides an illustration of the nature and importance of the composition effect for fixed-term households by plotting the impulse response functions for the Great Recession baseline experiment (in blue), and for the "no composition effect" experiment (in orange).[15] The baseline period (t=-1 on the plot) is 2007, while the Great Recession starts in 2008 (t=0 on the plot) and lasts for the whole plotted period. Fixed-term household's composition effect is subtle and evolves throughout the recession. The share of fixed-term contracts in the overall employed population is larger in recession that in boom. This implies that, in the first periods of the recession, the size of the fixed-term group grows (in the simulations, this is the case in the first two years of the recession). During this time, there is a flow of households transitioning from permanent contracts to fixed term contracts. On average, permanent workers have higher wealth and durables stock than their fixed-term counterparts. Consequently, at the start of the recession, the flow of permanent households into the fixed-term group brings up the group's average wealth and stock of cars. This composition effect can be seen in panels c and d of Figure 1.4 where average car stock and liquid wealth are larger in the baseline than in the experiment

[14] The permanent contracts that are captured in the fixed-term group are often households who spent the start of the year with a fixed-term contract and upgraded to a permanent one after June. These upgrades are less likely in recession.

[15] Plots of permanent households' impulse response functions can be found in Appendix C.

Figure 1.4. Impulse Response Functions (Fixed-term Households)



without composition effect. In the later part of the recession, when the size of the fixed-term group has stabilized, the change in its composition is only due to the larger share of unemployed households and (mostly) the lower share of permanent contracts.

Finally, the composition effect deepens the size of the car consumption drop along both adjustment margins. In the first part of the recession, the households who just transitioned from permanent contracts own a stock of cars that is too high compared to their current income and prospects. Consequently, they will not make new car purchases. For the later part of the recession and for the intensive margin, the lower share of permanent contracts in the fixed-term group reduces the adjustment frequency and the size of car purchases.

1.6 Policy Experiment: Car Purchase Subsidy

In 2009, the Italian government spent 2 billion euros in subsidies to support the automobile sector. To explore the consequences of such a policy, I use the model as a laboratory and investigate the impact a payment corresponding to 5% of car expenses during 2009. For the average car purchase, this corresponds to roughly €500. In the simulations, households did not anticipate the implementation of the subsidy. In 2009, they are aware of the programme, but they do not expect that it will last only for a year. It is important to note that, in this exercise, the programme is a "free lunch" as we are in partial equilibrium and there is no tax to finance the subsidy. Consequently, the results of the experiment cannot be directly compared to the reality. They provide an over-estimate of the positive impact of the policy.[16] Still, this exercise is informative of how much car subsidies can achieve (at best), and of the potentially heterogeneous impact on households exposed to different type of risk.

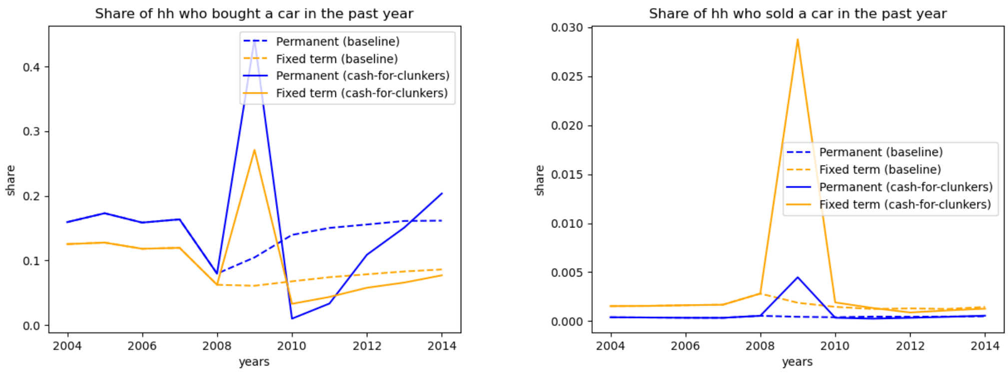
The left panel of Figure 1.5 shows the share of households who bought a car in a given year for the permanent group (in blue) and for the fixed-term group (in yellow). The solid lines represent the simulations with the 2009 car subsidy, while the dashed lines are the Great Recession baseline experiment. First, in 2009, the subsidy strongly increases the share of buyers (44% for permanent and 27% for fixed-term households). However, as soon as the policy ends, there is a reversal and the share of buyers significantly drops for the following couple of years. The car subsidy did not trigger net new purchases, but simply prompted households to anticipate their car investment. The timing of purchases was

[16] If we assume that the aim of the policy is to stimulate car consumption.

brought forward, leading to depressed car consumption in the post-programme period. This finding is consistent with the empirical analyses of Mian and Sufi (2012), Hoekstra, Puller and West (2017), and Green et al. (2020), who study the cash-for-clunkers policy in the US and find that its stimulative effect on car consumption occurs mainly by changing the timing of investments rather than by inducing additional purchases.

What is more, the car subsidy even deepened the drop in the value of car expenses on the intensive margin. In the baseline experiment, cars intensive margin decreases by 9% and 19% for permanent and fixed-term households respectively. With the car subsidy these numbers jump to 14% and 24%. In 2009, the subsidy implies that a much larger share of households buy a car. Therefore, the average distance between the current car and the target one (i.e. the value of the purchase) is much smaller. After 2009, households' target stock of cars is well below what they currently own, and they shift resources towards liquid assets. In summary, the car subsidy brings forward car investment while depressing the extensive margin of car consumption in future periods and failing to stimulate the intensive margin.

Figure 1.5. Car Purchase Subsidy



(a) Share of Buyers

(b) Share of Sellers

Finally, the impact of the subsidy depends on the type of risk faced by the households. In 2009, the spike in fixed-term households' car purchases is milder than that of their permanent counterparts. Following the collapse in their upside income risk, fixed-term household adopt a "wait-to-downgrade" strategy. Their aim is to lower their car holdings and therefore, the subsidy has limited ammunition to make them upgrade. Moreover, the subsidy can even be seen as a *downgrading subsidy*. The right panel of Figure 1.5 shows the share of households who downgraded their car in the year (i.e. sold their car to purchase a cheaper one). In 2009, a share of fixed-term households take advantage of the subsidy to downgrade their stock of cars.

1.7 Conclusion

This paper investigates the impact of risk heterogeneity on durable consumption over the business cycle. I examine household risk heterogeneity through the lens of employment contract type, and document that during the Great Recession, fixed-term contract workers reduced their car purchases significantly more than their permanent counterparts (along both the intensive and extensive margins). Using an incomplete market model with durable consumption and a dual labour market, I examine the drivers of the consumption patterns for each contract type. I find that, on the one hand, households that experienced an increase in downside income risk (such as permanent contract holders) adopted a "wait-and-see" strategy for their durable purchases during the Great Recession. On the other hand, households that experienced a decline in upside income risk (such as fixed-term contract holders) adopted a "wait-to-downgrade" approach to their durable spending. In addition, about 40% of the decline in fixed-term households' car consumption can be explained by a composition effect. Omitting this composition effect would lead to a significant overestimation of the car non-convex adjustment cost. Finally, a car purchase subsidy has a limited ability to stimulate durable consumption for households facing a decline in their upside income risk. The policy is *de facto* partly transformed into a *downgrading subsidy.* A direction for future research is to extend this framework to study the general equilibrium effects of sector-specific technological shocks on durable consumption.

1.A Appendix A: Data Appendix

1.A.1 Appendix A1: SHIW Data

This appendix provides additional discussion on the Survey on Households Income and Wealth (SHIW) conducted by the Bank of Italy between 1965 and 2020 (last available wave). I restrict my study to 2000-2014 because prior to 2000, the SHIW did not collect the data necessary for my analysis. From 2000, the SHIW provides detailed job-related characteristics, as well as information on households' income, wealth, non-durable consumption and durable goods expenditures. The SHIW also reports vehicles sales and purchases.

The survey is conducted every two years and has a panel component (that has been growing since its introduction and represents 55% of the sample in 2014). The units of observation are individuals and households. The sample size is approximately $8,000$ households and $20,000$ individuals in each wave. The survey provides sampling weights that are representative of Italian households and Istat computed monetary reevaluation coefficients.

The SHIW presents some advantages over American surveys that are often used to study durable consumption: the CEX and the PSID. The CEX has little information on households' characteristics and employment status, has a short panel element (households are part of the sample for a maximum of four consecutive quarters), and the frequency of income, wealth and consumption are not synchronised. On the other hand, the PSID also has a small sample size (2,000 households).

1.A.2 Appendix A2: Sample Selection

Sample selection: Household-level by type of contract. I restrict my analysis to households with at least one employed income earner aged between 20 and 65 years old, without any self-employed member and without any currently unemployed member. Additionally, my analysis is restricted to households where employed members have the same type of contract or households with a single income earner. I exclude other households as they are difficult to sort in the permanent versus fixed-term contract groups. Finally I exclude households with missing information on type of contract. In Boom, the sample counts roughly 500 households in the fixed-term group and 7,500 observations in the permanent group. In recession, the fixed-term and permanent groups respectively gather 1,050 and 9,050 observations. This sampling is used for all the household-level variables by type of contract. However, I make an exception when I compute the intensive margin of car purchases for fixed-term households. To have enough observations, I keep any household where at least one member holds a fixed-term contract, meaning that I keep households with two earners in different employment contract.

Sample selection: Household-level, all employment status. To compute population wide moments in the data, I restrict my analysis to households with at least one employed or unemployed member aged between 20 and 65 years old. I exclude household with any self-employed member.

Sample selection: individual-level. To study income and employment state transitions, I keep individuals currently employed or unemployed, aged between 20 and 65 years old, and who have been surveyed in at least two consecutive waves (three consecutive waves when I estimate the income risk process conditional on being employed). I exclude observations with missing information on the type of contract or missing income.

Sample selection: unemployed individuals. To recover unemployment benefit value and coverage, I select currently unemployed individuals who are aged between 20 and 65 years old. I exclude first-time job seekers as they do not qualify for unemployment benefits.

1.A.3 Appendix A3: Variables Treatment and Definitions

To remove outliers, I winsorise the top and bottom 1% (by boom/recession period and by type of contract) for all numerical variables. For household-level variables, households sampling weights are used. Cars and non-durable expenditures are deflated using CPI price indices (CPI for new cars and CPI for non-durable consumption respectively) . Other nominal variables are deflated using the Istat reevaluation index.

Definitions:

- **Car purchases (or stock)** encompass all means of transport including motorbikes and boats. In the data, the split between cars and other vehicles is available only from 2012 onward. For consistency, I keep cars and other vehicles as my measure of car purchases (or stock) throughout the entire period. This should not alter the results as between 2012 and 2014, cars represented more than 90% of all vehicles purchased by households. Car purchases (or stock) are normalised by dividing by OECD scale adult equivalent units.

- **Non-durable consumption** refers to all consumption expenditures excluding durable goods (cars, furniture, appliances). Non-durable consumption is normalised by dividing by OECD scale adult equivalent units.

1.A.4 Appendix A4: Summary Statistics

Table A4.1 provides some household-level summary statistics for 2002-2006 (before the Great Recession). Permanent households' average income and wealth is roughly twice as large as that of fixed-term households. Fixed-term households' heads are on average younger and less educated than the heads of permanent households. Finally, the share of fixed-term households is higher in the poorer regions of the South of Italy.

Appendix Table A4.1. Summary Statistics

	Permanent contract	Fixed-term contract
Mean income (€)	38774	20613
Mean wealth (€)	188168	94264
Mean age of head of hh	44	40
Share living in the North (%)	53	32
Share living in the Center (%)	21	13
Share living in the South (%)	26	55
Share of college graduates (%)	11	6
Share of high school graduates (%)	46	26
Share living in a small city i.e. - 40,000 inhab. (%)	57	60
Mean number of children	1.23	1.33

1.B Appendix B: Calibration

1.B.1 Appendix B1: Employment State Transitions

Note that the Perm. to Perm. transition in the first column does not imply that the worker stayed in a permanent employment for two full years. It simply means that, at the two survey dates, the worker was employed under a permanent contract (he could have gone through other employment states in-between the two surveys).

Appendix Table B1.1. Targeted Moments of the Employment Transitions

Boom

Target Transitions (2-year time horizon)	Data	Model
Perm. to Perm.	0.93	0.93
Perm. to F.T.	0.04	0.04
Perm to Unem.	0.03	0.03
F.T. to Perm.	0.49	0.49
F.T to F.T	0.36	0.36
F.T. to Unem.	0.15	0.15
Unem. to Perm.	0.23	0.23
Unem. to F.T.	0.15	0.15
Unem. to Unem.	0.62	0.62

Recession

Target Transitions (2-year time horizon)	Data	Model
Perm. to Perm.	0.90	0.90
Perm. to F.T.	0.06	0.06
Perm to Unem.	0.05	0.05
F.T. to Perm.	0.33	0.33
F.T to F.T	0.47	0.47
F.T. to Unem.	0.20	0.20
Unem. to Perm.	0.14	0.14
Unem. to F.T.	0.13	0.13
Unem. to Unem.	0.73	0.73

1.B.2 Appendix B2: Calibration of the Income Risk

I use the following restrictions to identify the persistent component's intercept, persistence and variance parameters:

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

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

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

$$E(\tilde{y_{it}}) = \frac{\tilde{\mu}}{1 - \tilde{\rho}}$$

The normalised income grids for each type of contract are displayed below.

Permanent contract:

$$\textbf{Income} = \begin{array}{c} \begin{matrix} y1 & y2 & y3 & y4 & y5 \end{matrix} \\ \begin{pmatrix} 0.55 & 0.74 & 1 & 1.34 & 1.81 \end{pmatrix} \end{array}$$

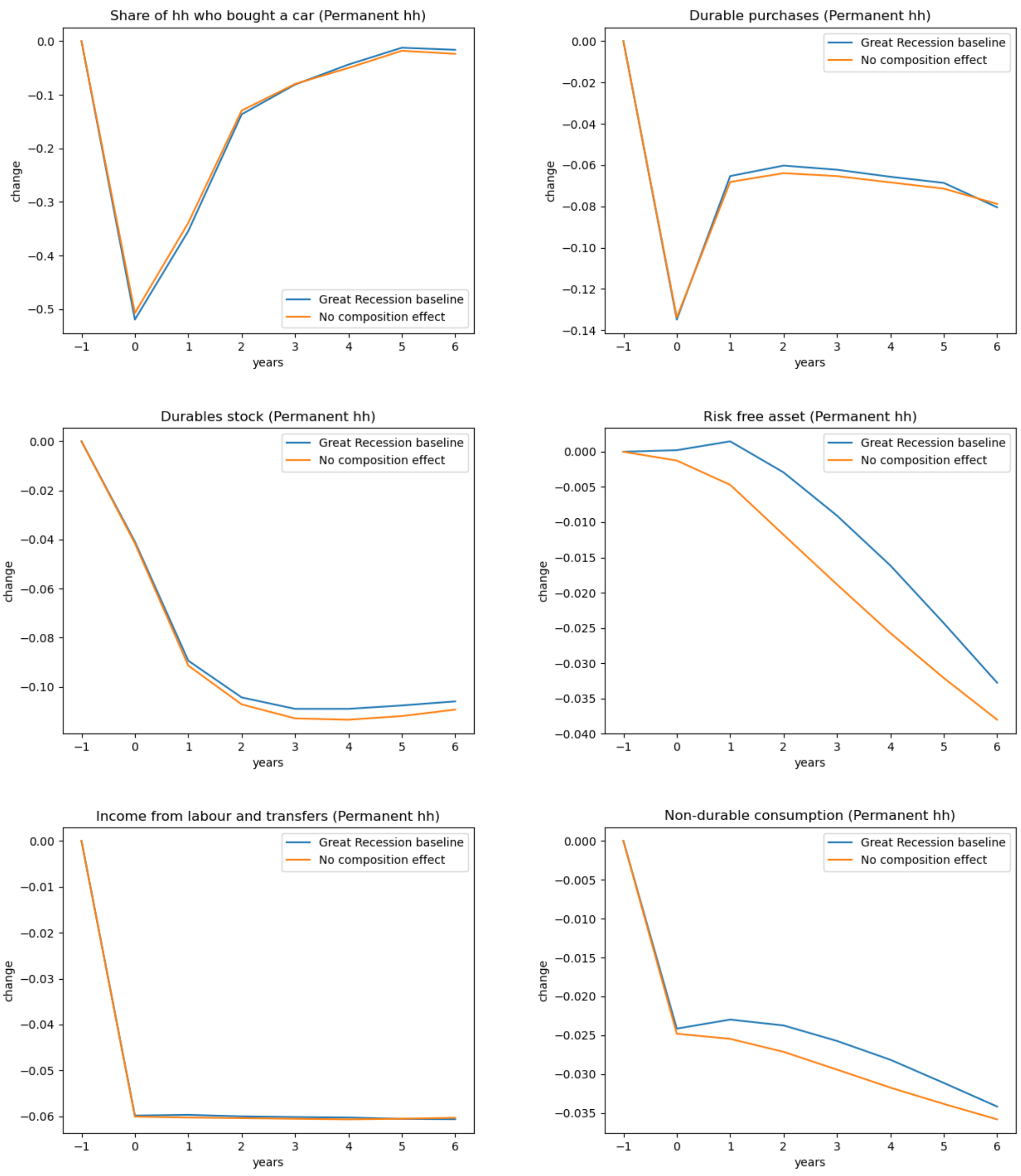
Temporary/Fixed-term contract:

$$\textbf{Income} = \begin{array}{c} \begin{matrix} y1 & y2 & y3 & y4 & y5 \end{matrix} \\ \begin{pmatrix} 0.27 & 0.36 & 0.48 & 0.65 & 0.87 \end{pmatrix} \end{array}$$

1.C Appendix C: IRFs (Permanent Households)

Figure C.1 displays permanent households' impulse response functions for the Great Recession baseline experiment (in blue), and for the "no composition effect" experiment (in orange).

Appendix Figure C.1. Impulse Response Functions (Permanent Households)



Chapter 2

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

2.1 Introduction

The recent rise in remote work has extended well beyond the period of the pandemic, reaching a large proportion of the workforce. In the UK for example, between September 2022 and January 2023, 44% of workers were still working from home. How does work-from-home (WFH) reshape household's housing demand? Should workers who cannot work from home care? Will WFH impact inequality in the short and long-run?

In this chapter, I provide a new theoretical framework to examine the impact of the rise in WFH on households. I build a dynamic heterogeneous agent model with endogenous WFH for some occupations, choice of housing tenure, and city geography. I investigate the effect of a rise in preference for remote work. In the model, house prices and rents are determined in equilibrium in each of the city location, allowing for general equilibrium effects of WFH induced changes in housing demand. The framework is used to quantify the impact of WFH in the long and short-run, using short-run empirical evidence to inform long-run model results. This bridges a gap in the literature as the existing empirical studies on the topic provide a short-run perspective by design, while the stylized models to date adopt a predominantly long-run approach. What is more, by modeling wealth accumulation and general equilibrium, it is possible to establish a direct link between the assets that are subject to demand and valuation changes, and the households who own them. This direct mapping has not yet been explored.

There are three main findings. First, in the model simulations, I show that WFH reshapes house prices by increasing the premium for space and reducing the commuting penalty. Second, in the long-run, the increase in WFH leads to the rise of a *tele-premium*. Workers in occupations where remote work is possible experience an increase in average income, consumption, housing, and liquid wealth. They also relocate from the city center to purchase larger properties situated in suburban areas. This shift can be viewed as a suburb-wide gentrification, in which those unable to work remotely are crowded out of homeownership. In the long-run, the consumption, housing wealth, and welfare of non-telecommuters decrease while overall consumption inequality rises. Third, even in the short-run, the welfare of the majority of non-remote workers decreases, despite their over-representation among suburban homeowners whose real estate has appreciated the most. This is due to decreased flexibility, the increase in the user cost of housing and the interplay between household heterogeneity and housing market frictions.

The model is a dynamic general equilibrium, heterogeneous agent model of remote work and housing tenure embedded in space. The main components are the following. **The city**: the model has two locations - the center and the suburb - that differ in amenities, commuting cost, land and housing supply elasticity. **The jobs**: some workers are employed in occupations where they can work from home. These workers choose how to allocate their working hours between the office (where they are more productive but have to commute) and their home (where they use some of their housing space in the production function). **The houses**: houses differ by their size, their location and their tenure (i.e households decide if they want to own or rent). Two realistic features of the housing market are included. First, to buy a house households need to provide a minimum down-payment. Second, selling properties is subject to non-convex adjustment costs. **Prices**: house prices and rents are determined in equilibrium in each location. Finally, the **incomplete market** feature enables the model to generate income and wealth distributions which interact with the financial frictions on the housing market. This enables the model to study housing affordability across the city.

Solving and parameterizing this complex model is challenging.[1] I use a solution method which combines the Discrete-Continuous Endogenous Grid Method with taste shocks (DC-EGM) of Iskhakov, et al. (2017) with the Nested Endogenous Grid Method algorithm (NEGM+) developed in Druedahl (2021). I parameterize the model to London and ensure that it is consistent with key features of the UK economy and the city of London before the rise in remote work (2016-2019). Crucially, the model is successful in matching the share of households who decide to live in the center - for the overall population, by occupation, and by income quintile.

To understand the impact of WFH on housing demand and households, I simulate a permanent shift in workers' preference for remote work. In the baseline economy, the preference for working from home is calibrated to match the share of total work supplied from home by workers employed in telecommutable occupations in the first wave of the UK time Use Survey (UKTUS, 2016). I then solve for a high remote work economy and transition period where the change in worker's preference for remote work is calibrated to match the observed WFH patterns during the transition phase (UKTUS, 2021). Modeling the rise in WFH as a change in preference is motivated by the Survey of Working Arrangements and Attitudes conducted by Barrero, Bloom, and Davis (2021) to investigate whether WFH will stick, and why. The authors find evidence of better-than-expected WFH experiences, and greatly diminished stigma

[1]The household problem has 6 states and 7 choices (some continuous and some discrete).

associated with remote work.[2]

I start by looking at the aggregate impact of the change in households' preference for remote work in the long-run (comparing steady states). I find that house prices and rents increase in both locations, but the rise is larger in the suburb, highlighting a change in housing demand with the rise in the demand for space and the decline in the commuting penalty. Aggregate labour rises by 2.5% because of savings in commuting time. The reduction in time spent commuting comes from two channels. First, the direct channel: workers in telecommutable occupations increase the share of their labour that is supplied from home, commute less, and are therefore able to supply more working hours overall. Second, the indirect channel: working-from-home increases the relative attractiveness of the suburb for households employed in telecommutable occupations. These workers do move away from the center to enjoy larger and cheaper houses, and make the most out of the reduced commuting costs. Consequently, space in the center is freed up for some workers in non-telecommutable occupations. These workers now also enjoy reduced commuting time and are also able to supply more working hours.

Beyond aggregate outcomes, remote work has heterogeneous implications across occupations with the rise of a *tele-premium*. Workers employed in occupations in which WFH is possible constitute the winning category in the long-run. These households' share of homeowners rises by 5 percentage points in the suburb and 3 points in the center. These workers also benefit from an increase in income, consumption, and liquid wealth. On the other end of the spectrum, the share of homeowners amongst households in non-telecommutable occupations decreases by 4 points (the drop is concentrated in the suburb).

[2] Another potential factor to explain to rise in remote work is an increase in productivity. I do not follow this approach as my model adopts a macro take on WFH with incomplete markets, non convexities, and rich multi-dimensional household choices. I am at the frontier of what can be solved numerically, therefore I do not model the positive agglomeration externalities from working at the office. Consequently, in my context, modeling WFH's rise as the result of a pure positive productivity shock would likely overestimate the associated output gains as I abstract from the counterbalancing force.

The mechanism at play is simple, the increased demand for suburban houses by telecommuting workers - who are on average high wealth and income households - leads the cheaper suburban properties to appreciate. The marginal homeowners are crowded out of home-ownership and turn to renting. This can be compared to a gentrification shock that hits all suburbs at the same time. On top of this large drop in real estate wealth, non-telecommuters also record a reduction in average consumption and welfare because of the higher house prices and rents throughout the city.

In addition to the *tele-premium*, WFH also impacts housing, liquid wealth, and consumption inequality in the overall population. In the long-run inequality changes, decreasing for liquid wealth while rising for consumption. Moreover, housing wealth inequality amongst homeowners is reduced because of two effects. Firstly, there is a valuation effect. House prices and rents in the periphery appreciate more than in the center. As the wealthiest households were those who owned properties in the center before the spread of remote work, the value of their asset decreases relative to that of more modest homeowners who had settled in the suburb. Secondly, there is a composition effect. The lowest income, lowest liquid wealth non-telecommuters have been crowded out of ownership and replaced by wealthier telecommuters. The group of homeowners is therefore richer and more homogeneous in the high WFH economy.

I then compute transitions between the two steady states to study how the economy evolves in the short-run. Most homeowners employed in non-telecommutable occupations owned houses in the suburb prior to the change in working arrangement. When remote work rises and suburban properties appreciate, a share of these owners sell their houses and realize capital gains before moving to the center. However, despite these gains, these households are not able to buy a property in the center because of the large difference in house prices across the two locations. They become renters, and build up some liquid wealth. This has a direct consequence on the shape of the price paths in the two locations over the transition. House prices in the center adjust gradually to reach the new steady state value because the new movers to the neighborhood are households whose housing demand takes some time to materialise. On the other hand, suburban house prices jump right away to the new steady state value. Households moving to the suburb are telecommuters who seek to buy large properties and are wealthy enough to purchase right away. The increase in demand for suburban properties is immediate, and prices rise to reflect it.

In term of welfare, the suburban homeowners who sold their house for a higher price at the start of the transition naturally experience welfare gains. However, these households represent a small share of the non-telecommuting owners. Interestingly, the remaining owners experience welfare losses during the transition as the user cost of housing increases and higher house prices and rents throughout the city decrease flexibility for households who want to move. Moreover, in order to benefit from the appreciation of their property, they must sell and pay non-convex adjustment costs. These expenses are particularly discouraging for low-income and low-wealth owners, who are over-represented among non-telecommuters. The welfare losses experienced by homeowners during the transition are the outcome of the interplay between household heterogeneity and housing market frictions.

Lastly, I use the model as a laboratory to study the implications of a policy that increases the supply of new houses in the center. An example of such a programme would be facilitating the conversion of commercial real estate into housing. The policy decreases house prices and rents in the center (compared to the no-policy baseline), and dampens the rise of house prices and rents in the suburb. Consequently, more non-telecommuters are able to relocate to the center, these households are more likely to become homeowners, and non-telecommuters' welfare losses associated with the rise in WFH are significantly reduced (for owners and renters, in the center, and in the suburb).

My work contributes to the strand of literature that investigates the impact of working-from-home on the housing market. It relates to studies that provide theoretical frameworks to understand how WFH changes housing demand and the city structure. These papers use urban economics models (Davis, et al. 2023, Delventhal and Parkhomenko 2023, Monte, et al. 2023, Delventhal, et al. 2022, Brueckner, et al. 2021) or a financial modelling approach (Gupta, et al. 2022). My study accompanies these papers as I incorporate endogenous housing tenure and household heterogeneity to the study of WFH and the city. Existing models have their focus elsewhere. The urban models developed in the literature do not model households' heterogeneity, nor wealth. The financial asset models are forward looking and fully transcribe the change in assets' value. However, they do not model the owners of the assets. This paper establishes the direct link between the assets that are subject to demand and valuation changes, and the households who own (or aspire to own) them. This is key in order to understand how the changes in housing demand and city structure affect the households residing in them. In this regard, it bears similarity to research undertaken on the affordability of cities and the well-being of their residents (Favilukis and Van Nieuwerburgh 2021, Favilukis, Mabille, and Van Nieuwerburgh 2022, Giannone, et al. 2023, Greany 2019).

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

The remainder of the chapter is structured as follows. Section 2.2 presents the model. Section 2.3 describes the parameterization strategy and the numerical implementation. Finally, the WFH experiment with the long-run analysis, the transitions, and the policy experiment is found in Section 2.4. Section 2.5 concludes.

2.2 The Model

2.2.1 Households

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

Preferences

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

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

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

Locations

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

Households' Labour

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

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

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

At the office, the worker produces efficient units of labour from the office,

n^O, determined by:

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

where A^O_t is a common productivity parameter for all workers at the office, ν is an idiosyncratic productivity shock assumed to follow a Markov process, and θ is the share of labour in the production process.[3]

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

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

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

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

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

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

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

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

Housing

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

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

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

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

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

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

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

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

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

Other Assets

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

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

where ι is an intermediation wedge.

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

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

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

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

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

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

2.2.2 Financial Sector

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

2.2.3 Rental Sector in Location j

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

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

2.2.4 Final Good Producer

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

$$Y_t = N^c_t$$

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

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

2.2.5 Construction Sector in Location j

The construction sector in area j solves:

$$\max_{I^h_{j,t}} p^h_{j,t} I^h_{j,t} - w_t N^h_{j,t}$$

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

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

The equilibrium housing investment in location j is:

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

2.2.6 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.

2.2.7 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.

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

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 $j = j'$:

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

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

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 $j \neq j'$:

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

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

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

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

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

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

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

2.2.8 Stationary Recursive Equilibrium

In the following section, variables indexed with the superscript h refer to households who start the period owning a house, and variables indexed with the superscript n refer to households who start without owning any real estate. To further ease notation, the vector of individual states for homeowners and non-homeowners are denoted as $x^h := (b,h,m,\nu,k,j) \in \mathbb{X}^h$, and $x^n := (b,\nu,k,j) \in \mathbb{X}^n$. A stationary recursive equilibrium is a set of decision rules $\{c^h, c^n, b'^h, b'^n, h'^h, h'^n, m'^h, m'^n, (\eta^H)^h, (\eta^H)^n, (\eta^O)^h, (\eta^O)^n, j'^h, j'^n, keep^h, sell^h, sellandbuy^h, sellandrent^h, buy^n, rent^n\}$, value functions $\{V^h, V^n, V^{keep}, V^{sell}, V^{rent}, V^{buy}\}$, prices $\{r, r_m, p_j^h, q_j\}$, aggregate variables (aggregate total efficient units of labour, final good sector efficient units of labour, and location specific rental units, stock of houses, construction sector efficient units of labour, and housing investment) $\{N, N^c, H_j^r, H_j, N_j^h, I_j^h\}$, 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 $\{c^h, c^n, b'^h, b'^n, h'^h, h'^n, m'^h, m'^n, (\eta^H)^h, (\eta^H)^n, (\eta^O)^h, (\eta^O)^n, j'^h, j'^n, keep^h, sell^h, sellandbuy^h, sellandrent^h, buy^n, rent^n\}$.

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

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

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 $N^c = N - \sum_{j=1}^{2} N_j^h$.

5. In each location j, the rental market clears at rent q_j and equilibrium

quantity of rental units H_j^r is:

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

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 satisfy:

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

where the left-hand-side represents inflows to housing stock on the market in location j from new constructions net of depreciation and sales of houses by homeowners. The right-hand-side represents outflows from the housing stock on the market from houses purchased by rental companies and by household buyers (who were renters or owners of a different house at the start of the period).

7. The final good market clears:

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

where the first two terms of the right-hand-side are expenditures in the final consumption good, the following term is the transaction costs when households sell their houses, and the next three terms represent collateralized debt inter-mediation costs (incurred by renters who bought a house, homeowners who kept their house, and homeowners who sold their house and bought a new one). Finally there are operating costs of rental agencies in each location, the government public good G that does not enter households' marginal utility, and net exports NX that are the losses/profits of the foreign financial agents who supply the safe asset and the collateralized debt.

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

2.3 Parameterization, Numerical Implementation and Decision Rules

2.3.1 Parameterization

I parameterize the model to be consistent with key features of the city of London and the UK economy before the rise in remote work (2016-2019). One period in the model is 2 years. I use a mixed parameterization strategy. A subset of parameters is fixed using standard values and the literature. Another set of parameters is calibrated to match moments from the UK economy outside the model. The remaining parameters are jointly calibrated using the method of simulated moments inside the model. The parameter values are summarized in Table 2.1. Table 2.2 shows the targeted moments.

Table 2.1. Parameters

Parameter	Value	Description	Target
Households - general			
β	0.9686	Discount factor	See Table 4
σ	2.00	Relative risk aversion	Standard value
γ	0.76	Weight of n.d.c. in utility	Davis, Ortalo-Magné 2011
σ_ϵ	0.05	Location taste shock scaling	13.5% of cross-location movers
χ^{WFH}	-0.3	Taste for WFH	See Table 4
ϵ_c	0.0665	Extra amenities - center	See Table 4
Households - housing			
ω	1.044	Utility bonus from owning	See Table 4
F^{sell}	7%	Selling cost	Kaplan, Mitman, Violante 2020
δ	1.5%	Annual depreciation rate	Kaplan, Mitman, Violante 2020
$h_{gridOwn}$	[1.92; 3.15; 5.15]	Grid for houses - owned	Kaplan, Mitman, Violante 2020
$h_{gridRent}$	[1.17; 1.92; 3.15]	Grid for houses - rented	Kaplan, Mitman, Violante 2020
Households - labour			
θ	0.82	Labour share in eff. units of labour	Valentinyi, Herrendorf 2008
h_{min}	0.45	Housing used to WFH	$10m^2$ office space
A^O	1.0	Pty. work from office	Normalisation
A^H	0.81	Pty. work from home	Gibbs, Mengel, Siemroth 2023
ρ	4.4	EOS WFH and WFO	Delventhal Parkhomenko 2023
χ_c	0.0953	Commuting cost - center	Davis, Ghent, Gregory 2023
χ_s	0.1766	Commuting cost - suburb	Davis, Ghent, Gregory 2023
	46%	Share of workers in tele. occ.	Davis, Ghent, Gregory 2023
Construction sector			
α_c	0.6	h. supply elast. - center	Saiz 2010
α_s	0.637	h. supply elast. - suburb	Saiz 2010
$\overline{L}$	0.311	Land permits (whole city)	Kaplan, Mitman, Violante 2020
	20%	Share land permits - center	surface - Inner London
	80%	Share land permits - suburb	surface - Outer London
Rental sector			
ψ	0.008	Rental cies. operating cost	Kaplan, Mitman, Violante 2020
Financial sector			
r	0.03	Interest rate	Annual interest rate of 3%
ι	33%	Intermediation wedge	Kaplan, Mitman, Violante 2020
λ_m	0.85	Debt collat. constraint	Greenwald 2018

Notes: All values are reported at the yearly frequency.

Table 2.2. Targeted Moments

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

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

Households - General

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

Households - Locations

The city in the model is calibrated to match the city of London. The center corresponds to the boroughs defined by the ONS as Inner London,[4] which approximately corresponds to Zones 1 and 2 of the London Underground service. The suburb represents the boroughs that the ONS defines as Outer London,[5]. The parameter corresponding to the extra amenities available in center, $\epsilon_c = 0.0665$, targets the ratio of house prices[6] in the suburb and the center. The scale parameter for the location specific extreme value shocks is set to 0.05, which implies that 27% of households change location at a two-year time horizon. This is consistent with the English Housing Survey for 2021-2022 where 28% of households expect to move more than 5 miles away from their current home in the next two years.

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

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

[6] Per square meter.

Households - Labour

In the utility function, the taste parameter associated with remote work, $\chi^{WFH} = -0.3$, is chosen to replicate the share of total work done from home of 15% in 2016 for workers employed in a telecommutable occupation. The parameter value is negative, consistent with Barrero, Bloom, and Davis (2021)'s who argue that, prior to Covid-19, working-from-home was associated with a social stigma. For efficient units of labour (at home and from the office), the share of labour in production, $\theta = 0.82$, is fixed using evidence from Valentinyi and Herrendorf (2008). The minimum housing space needed to be productive from home is set to represent a $10m^2$ office, that roughly corresponds to the average size of a room in central London.[7] Productivity at the office is normalized to 1, while productivity from work done at home is set to 0.81. This is chosen in line with evidence from Gibbs, Mengel, and Siemroth (2023) who study IT professionals and estimate that their productivity fell by up to 19% when they switched to WFH during Covid. The elasticity of substitution between WFH and work done at the office is set to 4.4 in line with Delventhal and Parkhomenko (2023)'s estimates. Following Davis, Ghent, and Gregory (2023), the commuting time for workers in the center in set to 25.7 minutes one way versus 47.7 minutes in the suburb. Finally, the stochastic productivity shock is modeled as an AR(1) process in logs calibrated with variance covariance identifying restrictions using the Annual Survey of Hours and Earnings between 2017 and 2019. The mean of the process is adjusted to be occupation specific. The resulting quarterly persistence is 0.97 and the variance 0.003. Additional details can be found in Appendix B.

Households - Occupations

In the model, workers can be employed in telecommutable or non-telecommutable occupations. I use the very detailed UK vacancy postings data from Hansen,

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

Lambert, Bloom, Davis, Sadun, and Taska (2023), which gives me access to the share of vacancies that explicitly allow workers to work remotely by 4-digit occupation code in 2019. I then sort the 4-digit occupations by intensity of work-from-home and construct the two occupation groups such that 46%[8] of the workforce belongs to the telecommutable category.

Households - Assets

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

Construction and Rental Sectors

Elasticities of housing supply are set within the range estimated by Saiz (2010) for the US. I set α_s to 0.635 in the suburb (corresponding to a housing supply elasticity of 1.75 which is the average value of Saiz's estimates). I assume that the elasticity is lower in the center and set $\alpha_c = 0.6$ (housing supply elasticity of 1.5). The operating cost of the rental companies, $\phi = 0.008$, as well as the amount of total land permits available in the city follow Kaplan, Mitman, and Violante (2020). Inner London represents around 20% of the city's surface, therefore, 20% of these land permits are issued in the center, and 80% in the suburb.

[8] Following Davis, Ghent, and Gregory (2023).

2.3.2 Non-targeted Moments

This subsection presents how the model's stochastic steady state fits some important moments that were not explicitly targeted in the calibration. Table 2.3 displays these cross-sectional moments in the model, and in the data.

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

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

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

2.3.3 Numerical Implementation

I solve for the model's policy functions by combining the DC-EGM with taste shocks of Iskhakov and coauthors (2017) with the NEGM+ algorithm developed in Druedahl (2021). These methods extend the endogenous grid point method of Carroll (2006) to economies with non-convexities and exploit the nested structure of problems. An additional layer of optimisation is attained with an enhanced interpolation method. I solve for households' policies on 400-

Table 2.3. Non-targeted Moments

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

Notes: Telec. stands for telecommuters, non-telec. for non-telecommuters, and inc. for income. Data source: ASHE 2019.

point grids for cash-in-hand and liquid assets, an 8-point grid for collateralized debt, and a 3-point grid for house sizes. Additionally, I discretize the autoregressive process for idiosyncratic productivity shocks into a seven states Markov process using the method proposed by Tauchen (1986). I iterate the value function until convergence using the absolute value of the largest difference as an error metric and a tolerance level of 1e-4. I solve the model in general equilibrium finding the two equilibrium prices - house prices in the center and in the suburb - with the Broyden algorithm.

2.3.4 Decision Rules

To understand the mechanisms at play in the model, it is useful to look at households' decision rules. Figure 2.1 plots households' probability to choose to live in the center over the distribution of liquid wealth.[9]

Panel a displays this decision rule for a household that starts the period without owning any real estate.[10] We first notice that the probability to choose

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

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

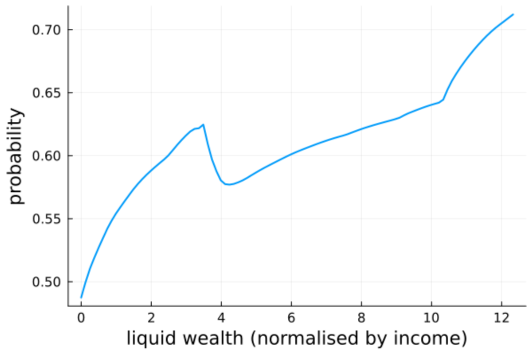
to live in the center is non-monotonic in liquid wealth. This is the case as this probability is obtained by comparing the expected value function in the center and in the suburb, and therefore interacts with the household's other location-specific decisions. The overall increasing pattern of the center probability over liquid wealth is expected. The center is on average the most attractive region because of the extra amenities and the lower commuting costs. These advantages are counterbalanced by higher house prices and rents. Therefore, when households get richer, they become more likely to pay the extra costs in order to enjoy the center's attractions. Note that the decision rule to live in the center has two kinks. Around a liquid wealth level of 4, the probability to choose the center drops. At this point, the household would actually be able to buy a house in the suburb, while they would remain a renter in the center. At the second kink (a wealth level a little bit above 10), the household would be able to be a homeowner in the center too. From this point on, the whole attractiveness of the center is restored, and the slope of the decision rule steepens.

Panel b, plots the same decision rule - the probability to live in the center - for two households, one that starts the period owning a house in the center (in blue), and one that starts the period owning a house in the suburb (in red).[11] First, we note that the probability to choose the city center is much higher for the household with the house in the center than for its suburban counterpart. This is the case as the owner in the suburb would need to sell their property in order to move. This is particularly costly because of the non-convex adjustment costs. Moreover, the gap between the probabilities of the two households narrows as liquid wealth increases. The reason for this is that the adjustment costs is particularly deterrent for lower levels of wealth, and loses some of its bite when households become richer. Finally, we note that the neighbourhood household specific taste shocks prevent the probability to choose the center to reach one. These mechanisms are intuitive and provide a

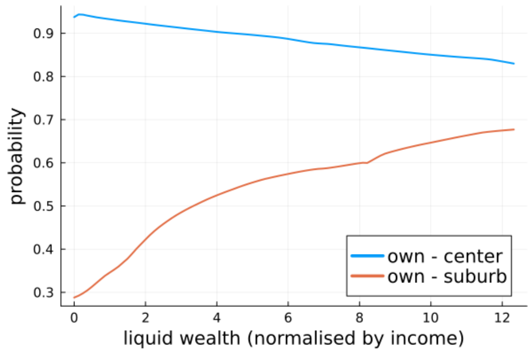
[11] More precisely, these are households with median income, median housing wealth, no collateralized debt, and employed in a telecommutable occupation.

sanity check for the model.

Figure 2.1. Decision Rules: Probability to Choose the Center



(a) Non-homeowners



(b) Homeowners

Notes: The households are employed in a telecommutable occupation, and have median income. The owners have median housing wealth, and no collateraized debt. Liquid wealth is expressed normalised by the average biannual income in the economy.

2.4 Results: the Work-from-Home Experiment

2.4.1 Change in Preference

I now simulate the impact of a permanent shift in the preference parameter associated with remote work. In the baseline, the WFH preference parameter is calibrated to match the 15% 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 wave of the UKTUS (2021), the share of total work done from home by workers in telecommutable occupations jumps to 53% (a little bit more than 2.5 days a week). The preference parameter associated with this amount of WFH two years after the shock is $\chi^{WFH} = 0.07$. Here the change in preference parameter is calibrated to reproduce the patterns of WFH over the transition period. Intuitively, workers were forced into adopting remote work during the lock-downs, and many found a lot to like about it (e.g. working from the comfortable environment of their own home, spending more time with their partner or their pet...).

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

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

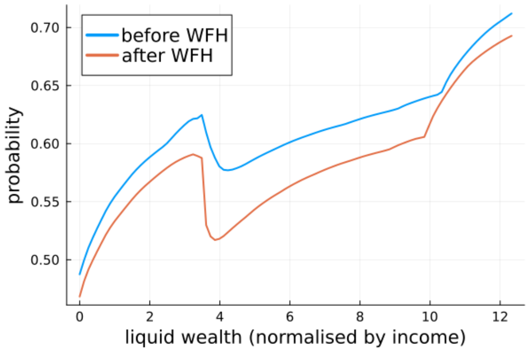
2.4.2 Long-run Analysis: the Rise of the *tele-premium*

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

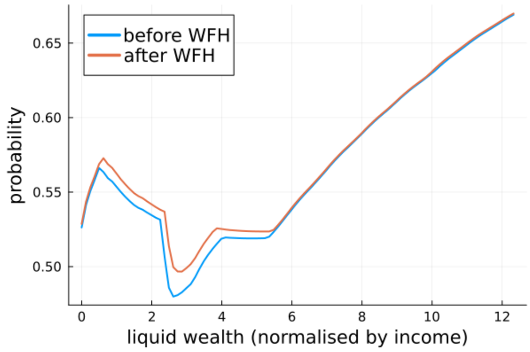
Figure 2.2 plots households' probability to choose to live in the center over the distribution of liquid wealth in the first steady state (in blue), and in the second steady state (in orange). Panel a displays this decision rule for a household employed in a telecommutable occupation who starts the period without owning any real estate.[12] Panel b displays this decision rule for a household employed in a non-telecommutable occupation who starts the period without owning any real estate.[12] This exercise provides a sanity check. For the household who can WFH, the probability to move to the center is lower in the high WFH steady state, the opposite is true for the household who cannot telecommute.

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

Figure 2.2. Decision Rules: Probability to Choose the Center



(a) Telecommutable Occupation



(b) Non-telecommutable Occupation

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

Aggregate implications: Remote work is associated with higher aggregate labour supply (+2.5%) in the second steady state because of savings in commuting time. This finding is consistent with Barrero, Bloom, and Davis' (2021) who state that "*the conventional approach* [to evaluate productivity gains] *ignores time spent commuting, which misses much of the gain associated with a shift to WFH*".

The savings in commuting time come from two channels. First, the direct channel: workers in telecommutable occupations significantly increase the share of their labour that is supplied from home, and are therefore able to supply more working hours overall. Second, remote work also reduces commuting costs via an indirect channel. Working-from-home increases the relative attractiveness of the suburb for households employed in a telecommutable occupation. These workers do move away from the center to enjoy larger and cheaper houses, and make the most out of the reduced commuting costs. Consequently, relative house prices and rents change across the city, and space in the center is freed up for some workers in non-telecommutable occupations. These workers now also enjoy reduced commuting time, and are also able to supply more working hours. The share of the center population employed in a telecommutable occupation decreased by 3 points between the two steady states (going form 50%

to 47%). Note here that I do not model leisure, therefore all the time that is not commuted is worked. However, my results are consistent with Barrero, et al.(2021) who repport that Americans devote around 95% of their savings in commuting time to work related activities.[13]

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

Winning category - The impact on households in a telecommutable occupation: Following the change in preference associated with WFH, telecommuters re-optimize their tenure and neighborhood decisions. The upper part of Table 2.4 displays telecommuters' tenure and location in the first steady state, and in the second steady state. The share of these households who own a house in the suburb rises by 5 percentage points in the long-run, going from 41% to 46%. The share of homeowners in the center also rises by 3 percentage points, bringing overall telecommuters' home-ownership rate to 63%, against 55% in the baseline steady state. These changes in how much telecommuters own and where they live reflect the increased housing demand, and the drop in commuting costs. Moreover, the share of households employed in a telecommutable occupation

[13] 35% to their primary job, and 60% for other work related activities.

that rent in the suburb shrinks by 20%. This indicates that the telecommuters are thriving in the new steady state because the suburban renters represent the most disadvantaged group in the economy, with mean consumption and liquid wealth less than 75% and 70% of the population averages.

Moreover, between the two steady states, telecommuters' average labour income rises by 5%[14], consumption by 7%, liquid wealth by 5%, and real estate wealth by 16%. These gains span the whole population of telecommuters. For instance, panels a and b of Figure 2.3 plot telecommuters' consumption and housing wealth distributions. We note a rightward shift in both distributions between the first steady state (in blue), and in the second one (in orange).

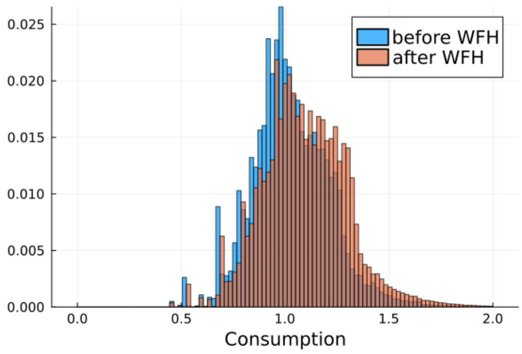
Table 2.4. Location and Tenure Allocations

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

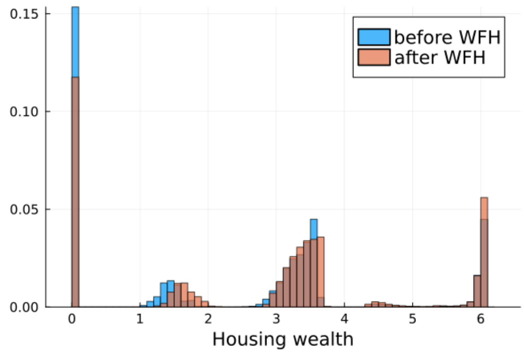
The impact on households in a non-telecommutable occupation: Like their telecommuting counterparts, households employed in a non-telecommutable occupation change their location and tenure decisions between the two steady states. The lower half of Table 2.4, shows a significant drop in the share of non-telecommuters who own a house in the suburb (4 percentage points, from 39% to 35%). If telecommuters increase their overall home-ownership rate between the two steady states, the opposite is true for the non-telecommutable occu-

[14]Because of longer working hours and some degree of complementary between WFH and work at the office.

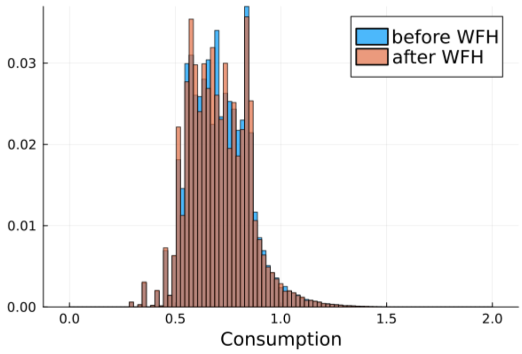
Figure 2.3. Distributions in the Two Steady States



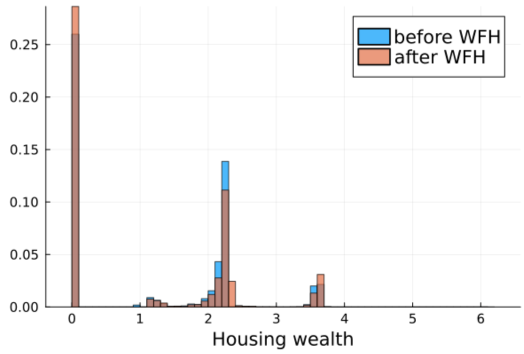
(a) Consumption (Telecommuters)



(b) Housing Wealth (Telecommuters)



(c) Consumption (Non-telecommuters)



(d) Housing Wealth (Non-telecommuters)

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

pation. The 4 percentage points drop in suburban home-ownership is paired with a 4 percentage points increase in the share of renters. The mechanism at play is simple. In the suburb, properties are cheaper (recall that in the baseline steady state, the house prices ratio in the suburb relative to the center is 0.62), therefore they are held by the least wealthy amongst homeowners. The increased demand for suburban houses by telecommuting workers - who are on average high wealth and income households - leads the formerly cheap suburban properties to appreciate. The marginal homeowners become unable to afford them, and are crowded out of home-ownership and forced into renting. Table 2.5 illustrates this point by displaying the location and tenure probability in the 2 steady states for the marginal non-telecommuter buyer in the baseline economy.[15] The marginal non-telecommuter buyer is an household who starts the period without owning any real estate, whose liquid wealth equals the population's 60th percentile, and whose income is at the median. In the first steady state, this marginal buyer will purchase a house in the suburb with probability 0.49, and become a renter in the center with probability 0.51. In the new steady state, this same household is crowded out of the owner occupied housing market, rents in the suburb with probability 0.46, and rents in the center with probability 0.54. The increase in telecommuters' housing demand in the suburb and the pricing out of the least wealthy owners and buyers can be compared to a gentrification shock that hits the whole periphery at the same time.

Table 2.5. 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	0.49	0.51	0.0
After WFH	0.0	0.0	0.54	0.46

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

Moreover, non-telecommuters' average income rises by 0.1% (because of the lower commuting for those who managed to reallocate to renting in the center), but their average housing wealth drops by 7% and their mean consumption by 0.4% (because of the increased house prices and rents). Once again, this is not only the case for average values, but holds along the distributions. Panels c and d of Figure 2.3 show a small leftward shift in non-telecommuters' consumption and housing wealth distributions.

Finally, Table 2.6 shows the welfare losses experienced by non-telecommuters after the rise in WFH. Welfare is computed in terms of compensating consumption variation, which is the amount of extra consumption that should be given to households in the second steady state in order for their utility to be the same as

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

before the rise in remote work. It is expressed as a percentage of second steady state consumption. Positive values indicate that households should receive additional consumption to be indifferent towards remote work, and therefore imply a welfare loss. We note here, that computing welfare with a utility based measure and comparing it across the two steady states would be an unfair exercise for the telecommuters' group. It is the case because these households experienced a change in a preference parameter between the two economies, making utility-based welfare comparisons uninformative. However, this issue does not apply to the workers employed in non-telecommutable occupations as they cannot work from home. Their preference and utility parameters remained the same throughout the experiment and the change in their utility is informative of their welfare across the two steady states.

Table 2.6. Welfare of the Non-telecommuters (Compensating Consumption Variations)

Non-telecommuters	Consumption Variation
All non-telecommuters	**2.8%**
Renters	**3.9%**
Renters - Center	3.9%
Renters - Suburb	3.8%
Owners	**1.45%**
Owners - Center	1.42%
Owners - Suburb	1.46%

Notes: The consumption compensating variations measure the amount of additional consumption that should be given to households after the rise in WFH in order for their utility to be the same across the two steady states. A positive value, indicates that the household should receive extra consumption in order to be indifferent towards the rise in remote work, and therefore corresponds to a welfare loss. Consumption variations are expressed in percentage of second steady state consumption. This analysis is conducted for non-telecommuters only as it is based on comparing utility between the two steady states. This would be an unfair exercise for telecommuters who experienced a change in taste.

Overall, non-telecommuters record a drop in welfare, and they would need to receive a consumption boost of 2.8% in the second steady-state to be indifferent towards the rise in WFH. The welfare loss is stronger for renters (3.9% in consumption equivalence) who are already at the lower end of the consumption and welfare distributions. This welfare loss is induced by the larger rents across the city reducing resources available for consumption and saving. Surprisingly, homeowners also record a welfare loss (1.45% in consumption equivalence), and this is true even in the suburb where properties appreciated the most (1.42% in consumption equivalence). Owners experience welfare losses because of the rise in the user cost of housing[16] and because larger house prices and rents across the city reduce their flexibility if they wanted to move house or change location. Moreover, for homeowners to benefit from the capital gains associated with the rise in house prices, they would need to sell their property. However, the non-convex adjustment costs make selling houses particularly costly, and the rise in prices is not large enough to compensate for these selling costs. These non-convex selling costs are particularly discouraging for low income low wealth households who are over-represented amongst non-remote workers.

Let's note here that the long-run welfare losses incurred by non-telecommuters could potentially impact workers' occupation choices. In the current model, I fully abstract from this margin as occupations are exogenous and permanent. While I acknowledge this limitation, the current version of the model is at the frontier of what can be solved numerically. However, I understand the importance of occupational choices in the context of remote-work and I will explore this avenue in future work.

***Tele-premium* and long-run inequality:** The rise in remote work has strong implications on where households live and on their tenure decisions in the long-run. Consequently, it also has implications for consumption, wealth, and real estate inequality - both across occupations and in the overall population. Table 2.7 shows the *tele-premium* and several measures of consumption, housing, and wealth inequality in the two steady states.

The top part of the table shows *tele-premia* defined as the average consump-

[16]Maintenance costs are proportional to house prices.

tion (or housing/liquid wealth) of the telecommuters over the average consumption (or housing/liquid wealth) of the non-telecommuters. Since the rise in remote work, the *tele-premia* in consumption, housing, and liquid wealth have substantially increased. For instance telecommuters' housing wealth is roughly equal to twice that of the non-telecommuters in the first steady state, against 2.5 after the rise in remote work.

The lower part of Table 2.7 displays several inequality measures in the overall population. Consumption inequality rises across the three different measures. For instance, the ratio of average consumption of owners to renters goes from 1.18 to 1.25 across the two economies. The rise in consumption inequality is driven by higher rents and house prices, as well as larger income for the part of the population able to telecommute. Liquid wealth inequality decreases in the overall population, but rises between renters and homeowners. Finally, we note that for housing, the 90th percentile to median ratio is lower in the high WFH economy, meaning lower housing wealth inequality amongst homeowners. This drop in the housing wealth discrepancy in the intensive margin is explained by two factors. On the one hand, there is a valuation effect. As the wealthiest households were owning properties in the Central Business District before the spread of remote work, the value of their asset decreased relative to that of more modest homeowners who had settled in the suburb, lowering inequality. On the other hand, housing wealth inequality for homeowners drops because of a composition effect. The lowest income, lowest liquid wealth telecommuters have been crowded out of ownership and replaced by wealthier telecommuters. The group of homeowners is therefore richer and more homogeneous in the high WFH economy.

2.4.3 Transitions

The previous section identifies some winning and losing categories of households in the long-run. However, across the distribution, the impact of the rise in remote work depends on accounting for transitional dynamics. Here, I compute

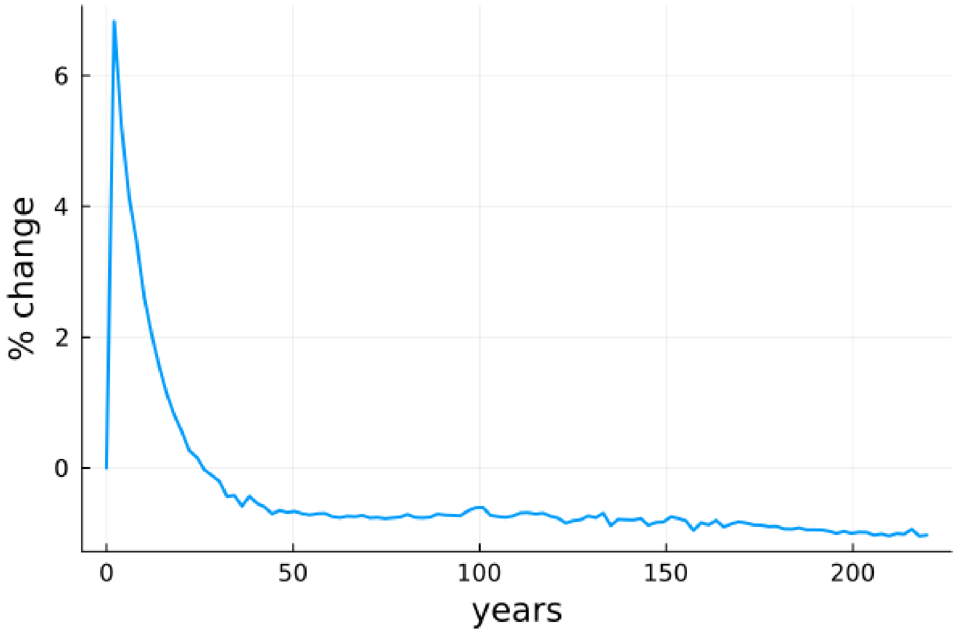
Table 2.7. Consumption, Housing, and Liquid Wealth Inequality

tele-premium	Before WFH	After WFH
Consumption	1.45	1.55
Housing wealth	1.98	2.47
Liquid wealth	1.32	1.37
Overall Inequality	Before WFH	After WFH
Consumption		
90th/10th ptile	1.40	1.48
90th ptile/median	2.05	2.20
owners/renters	1.18	1.25
Housing wealth		
90th ptile/median	1.83	1.73
Liquid wealth		
90th/10th ptile	2.98	2.86
90th ptile/median	17.57	16.98
owners/renters	1.08	1.12

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

the transition paths between the two steady states non-linearly, solving for the equilibrium sequence of prices over the whole transition period.

Figure 2.4. Share of Sellers over the Transition



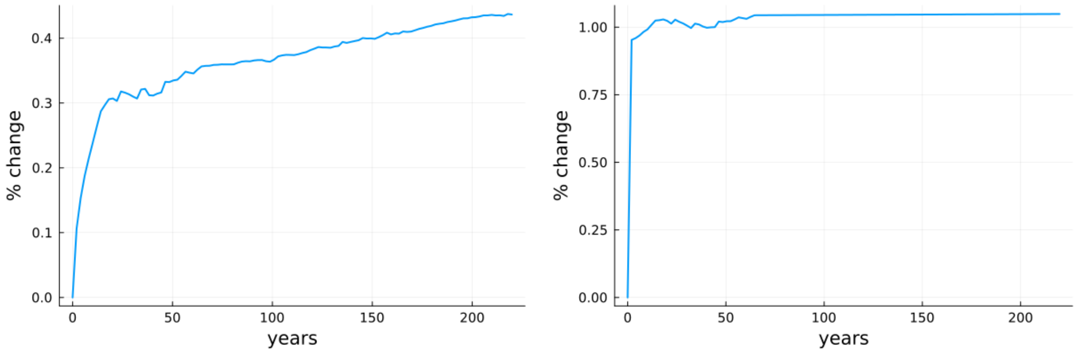
Notes: This figure displays changes in the share of sellers amongst homeowners in non-telecommutable occupations.

Figure 2.4 plots the changes in the share of homeowners employed in non-telecommutable occupations who decide to sell their house over the transition. When the change in taste for remote work arises, the share of sellers rises by 6% before converging to the new steady state value (that is slightly below the first steady state). Most homeowners employed in a non-telecommutable occupation own houses in the suburb prior to the change in working arrangement.[17] These households own the properties that appreciate the most with WFH. The extra sales are therefore realised by suburban owners who respond to the increased demand coming from wealthy telecommuters. These sellers then move to the center. However, the capital gains from their sale does not allow them to directly buy in the center because of the large difference in house prices across the two locations. Therefore, they become renters in the center, and build up some liquid

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

wealth. Conditional on good income shock realisations, they will eventually access home-ownership in the center.

Figure 2.5. House Prices Paths over the Transition



(a) Center (b) Suburb

This has a direct consequence on the shape of the price paths in the two locations over the transition. Figure 2.5 plots house prices' path for the center in panel a, and the suburb in panel b. The house prices in the center adjust gradually over the transitional period. This is because the new movers to this area are the households who just sold their house to telecommuters, and whose housing demand materialises later in the transition. Therefore, house prices in the center take longer to rise. On the other hand, suburban house prices adjust very rapidly to the new steady state value. Households moving to the suburb are telecommuters who seek to buy large properties to work from home. These households are wealthy enough to buy right away. The increase in demand for suburban properties is immediate, and prices rise to reflect it.

Taking into account the transition period is key when analysing welfare implications for households who owned real estate before the rise in remote work. Naturally, the suburban homeowners who sold their house for a higher price at the start of the transition experience welfare gains. However these households represent a small share of the non-telecommuting owners. Table 2.8 shows welfare compensating consumption variations over the transition period. I compute welfare for the "Median Owner" in each location (homeowners with median liquid wealth, median income, and median housing wealth). Surprisingly, these median owners experience welfare losses over the transition period despite owning assets that appreciated. This is explained by the decreased flexibility if they wanted to change house or location[18], the rise of the user cost of housing[19] and the interaction between household heterogeneity and housing market frictions. In order to benefit from the increased value of their house, households should sell. However the non-convex adjustment costs make selling property particularly costly. These selling costs are particularly discouraging for low-income and low-wealth owners, who are over-represented among non-telecommuters.[20] Therefore, non-telecommuting owners are particularly reluctant to sell their property and experience welfare losses even after a positive change in their asset's value.

Table 2.8. Welfare of Non-telecommuters (Compensating Consumption Variations)

Non-telecommuters	Incl. Transition
"Median Owner" - Center	2.09%
"Median Owner" - Suburb	2.23%

Notes: The consumption compensating variations measure the amount of additional consumption that should be given to households after the rise in WFH in order for their utility to be the same across the two steady states, including the transition period. These are computed for the "Median Owner" in each location (homeowners with median liquid wealth, median income, and median housing wealth). A positive value, indicates that the household should receive extra consumption in order to be indifferent towards the rise in remote work, and therefore corresponds to a welfare loss. Consumption variations are expressed in percentage of first steady state consumption. This analysis is conducted for non-telecommuters only as it is based on comparing utility between the two steady states. This would be an unfair exercise for telecommuters who experienced a change in taste.

Finally, Figure 2.6 displays the *tele-premia* in consumption (Panel a), housing wealth (Panel b), and liquid wealth (Panel c) over the transition. The main takeaway is that the liquid wealth *tele-premium* changes sign overtime.

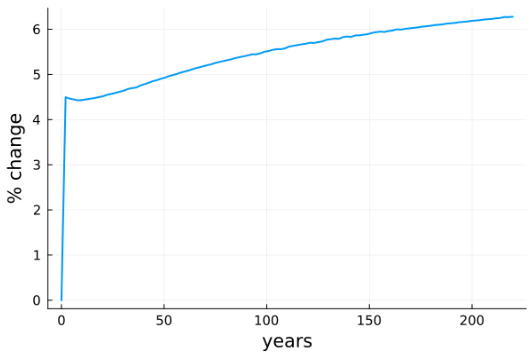
[18]As house prices and rents increased everywhere across the city.

[19]Maintenance costs are proportional to house prices.

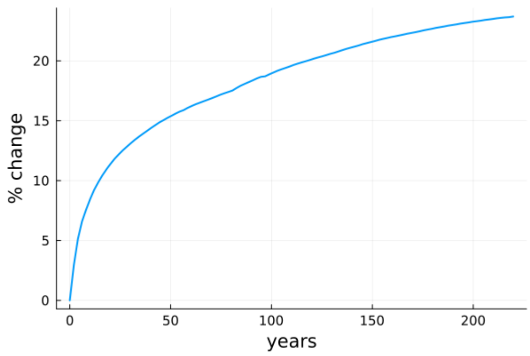
[20]For instance, non-telecommuters represent around 30% of sellers while they account for half of owners.

While liquid wealth inequality between occupations increases in the long-run, the opposite is true over the transition period. The rise in telecommuter's taste for space leads them to shift their portfolio towards real estate. Eventually, once they have reached the desired housing wealth level, telecommuters start to increase their savings in liquid wealth again. On the other hand, non-telecommuters' housing sharply drops when the taste for WFH changes (as more of these households sell and fewer buy). These extra resources not allocated to real estate at the start of the transition are used to build a liquid wealth buffer. Because of the permanent increase in housing costs across the city, the reduction in liquid wealth inequality does not translate into more equal consumption during the transition.

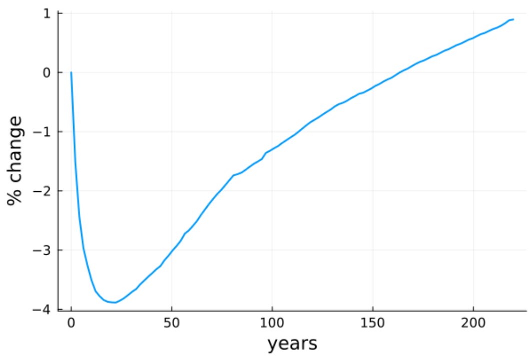
Figure 2.6. *Tele-premia* over the Transition



(a) Consumption



(b) Housing Wealth



(c) Liquid Wealth

Notes: *Tele-premia* refer to the average consumption (or housing/liquid wealth) of telecommuters over the average consumption (or housing/liquid wealth) of non-telecommuters.

2.4.4 Policy Experiment: Office-to-Apartment Conversions

Lastly, I use the model as a laboratory to study the implications of a policy that increases the supply of land permits in the center by 5%. An example of such a policy would be facilitating the conversion of commercial real estate into housing. The increase in WFH has led to a mismatch in the real estate market. Specifically, there is an oversupply of urban office and office-oriented retail, and insufficient residential properties. The conversion of offices into apartments is subject to rigorous regulation in the UK. These regulations have been a matter of policy debate and were recently relaxed in March 2021, yet they remain significant.[21] My current framework does not explicitly model commercial real estate, but increasing the amount of land permits in the center (where commercial real estate concentration is the largest) provides a reduced form approach to analysing the effects of loosened conversion regulations.

I reproduce the baseline experiment (i.e. rise in taste associated with remote work), but I now solve for the high WFH steady state increasing the amount of land permits in the center by 5%. I then compare this policy experiment to the baseline one. Increasing the availability of central land permits not only decreases house prices in the centre, but also weakens the rise in house prices in the suburb. In the baseline experiment, remote work triggers a 0.5% rise in steady state house prices in the center, and a 1% rise in suburban prices. In the policy experiment, center house prices decrease by 0.3%, and suburban properties appreciate by only 0.4%. This has three main implications for households. First, the decrease in central house prices and rents enables more non-telecommuters to relocate to the center after the rise in remote work. The share of non-telecommuters amongst the households living in the center increases by 3 percentage points between the two steady states in the baseline experiment, and by 3.5 percentage points in the policy experiment. The pol-

[21] For example, a building can only qualify for residential conversion if it has been a Class E building (broad category of commercial, business and service uses) for a minimum of two years. Similarly, an application for conversion can only be made if the property has been completely vacant for more than three months.

icy enables more workers in non-telecommutable occupations to benefit from reduced commuting costs. Second, with the policy, the non-telecommuters who relocate to the center are more likely to access home-ownership. The share of non-telecommuters owning a house in the center is stable in the baseline experiment, while it increases by two percentage points with the policy change.[22] Third, the lower house prices and rents reduce housing expenses. This is particularly important for households at the bottom of the income and wealth distributions. Table 2.9 illustrates this point by displaying welfare losses experienced by non-telecommuters after the rise in WFH in the baseline experiment (Column 1), and in the policy experiment (Column 2). Once again, welfare losses are expressed in consumption compensating variations and represent how much extra consumption should be given to households for them to be indifferent towards the rise in WFH. Positive values indicate welfare losses and the compensating variations are expressed in percentage of second steady state consumption. Increasing the availability of land permits in the center considerably reduces non-telecommuters' welfare losses. The policy reduces welfare losses by a factor of roughly 10 for owners and renters alike, both in the center and in the suburb.

[22] See Appendix C for the location and tenure allocations in the baseline and the policy experiments.

Table 2.9. Welfare of the Non-telecommuters (Policy Experiment)

Non-telecommuters	Consumption Variation	Consumption Variation (Pol.)
All non-telecommuters	**2.8%**	**0.3%**
Renters	**3.9%**	**0.4%**
Renters - Center	3.9%	0.4%
Renters - Suburb	3.8%	0.3%
Owners	**1.45%**	**0.2%**
Owners - Center	1.42%	0.2%
Owners - Suburb	1.46%	0.2%

Notes: The first column is a repetition of Table 8. Pol. stands for policy experiment. In the second column, the compensation variations are computed between the first steady state and a second steady state that includes a 5% rise in the supply of center land permits. The consumption compensating variations measure the amount of additional consumption that should be given to households after the rise in WFH in order for their utility to be the same across two steady states. A positive value, indicates that the household should receive extra consumption in order to be indifferent towards the rise in remote work, and therefore corresponds to a welfare loss. Consumption variations are expressed in percentage of second steady state consumption. This analysis is conducted for non-telecommuters only as it is based on comparing utility between the two steady states. This would be an unfair exercise for telecommuters who experienced a change in taste.

2.5 Conclusion

This chapter explores 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 worker's commuting costs. Households are impacted differently depending on whether they can partake in remote work or not, and on where they stand in the income and wealth distributions. In the long-run, there is the rise of a *tele-premium*, meaning some extra benefit for workers employed in occupations where remote work is feasible. What is more, WFH triggers suburb-wide gentrification, and while wealthy telecommuters buy larger houses in suburban areas, it crowds out the marginal owners and pushes them into renting. Long-run consumption inequality rises. Taking into account the transition period is key when analysing welfare implications for households who owned real estate before the rise in remote work. Surprisingly, in the short-run, the welfare of the majority of non-remote workers decreases, despite their over-representation among suburban homeowners whose real estate has appreciated the most. This is due to a decreased flexibility to change house or location, the rise in the user cost of housing and the interplay between household heterogeneity and housing market frictions. Finally, policies aiming at increasing the housing supply available in the center (e.g. facilitating office-to-apartment conversions) significantly reduce the welfare losses experienced by non-telecommuters after the rise in remote work. The model developed in this chapter 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 like modelling 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.

2.A Appendix A: Recursive Formulation of the Problem (Household who does not Own a House at the Beginning of the Period)

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

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

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

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

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

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

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

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

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

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

2.B Appendix B: Calibration of the Stochastic Productivity Process

The idiosyncratic productivity process is calibrated using the Annual Survey of Hours and Earnings 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 worker's observable characteristics. Hourly wage residual $\tilde{y_{it}}$ has a persistent component P_{it} which follows an auto-regressive process of order one, and some i.i.d measurement error ϵ_{it} (that I discard). 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 dummies for year, full time employment, job tenure longer than one year, and type of firm (private, public or non-profit). I then use the following variance covariance identifying restrictions to recover the persistent component's AR(1) parameters:

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

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

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

I then discretize the process into a seven states Markov process with Rouwenhorst method. Ultimately, the mean is adjusted so that the average productivity of workers in non-telecommtable occupations is 77% of that of workers employed in telecommutable occupations (in 2019, the average hourly wage of workers in non-telecommtable occupations is 77% of that of workers in telecommutable occupations).

2.C Appendix C: Policy Experiment Location and Tenure Allocation

Appendix Table C.1. Location and Tenure Allocations (Policy Experiment)

Share of households	Before WFH	After WFH	After WFH (Pol.)	Change	Change (Pol.)
Telecommutable occ.					
Own - Center	14%	17%	18%	$+3pts$	$+4pts$
Own - Suburb	41%	46%	46%	$+5pts$	$+5pts$
Rent - Center	30%	25%	24%	$-5pts$	$-6pts$
Rent - Suburb	15%	12%	12%	$-3pts$	$-3pts$
Non-telecommutable occ.					
Own - Center	8%	8%	10%	$-$	$+2pts$
Own - Suburb	39%	35%	34%	$-4pts$	$-5pts$
Rent - Center	30%	32%	32%	$+2pts$	$+2pts$
Rent - Suburb	23%	25%	24%	$+2pts$	$+1pt$

Notes: Columns 1, 2, and 4 are a repetition of Table 6. Pol. stands for policy experiment. The location and tenure allocation of households is displayed for the first steady state in Column 1, for the baseline second steady state in Column 2, and for the second steady state including a 5% rise in the supply of center land permits in Column 3. Column 4 shows changes between the first and the baseline second steady state. Column 5 shows changes between the first and the policy experiment second steady.

Chapter 3

Work-from-Home and the London Housing Market

3.1 Introduction

Chapter two uses a theoretical framework to examine how the recent growth in remote work impacts housing demand, households' welfare, and income, consumption and wealth inequality. A testable result of this analysis is that work-from-home (WFH) has reshaped households' housing demand by increasing the space premium and reducing the commuting penalty.

In this chapter, I provide novel empirical evidence for the city of London to validate this result. To conduct the empirical analysis I use real estate data at the property-level that provide a mapping between house prices and rents, and detailed dwelling characteristics. These data come from a linking of three datasets and capture the universe of residential properties sold in the United Kingdom since 1995, as well as properties available for rent on the Zoopla website between 2012 and 2021 for England and Wales.

First, I find that larger properties and properties located further out from London's city center have appreciated the fastest since February 2020. This is observed in both house prices and rental markets. For instance, between February 2020 and June 2022, the average price of large houses (5 rooms or more) increased by 20%, while that of small ones (studio or 1 room) dropped by 1%. Moreover, in the same period, the average price of properties located in central London (within a 5-kilometers radius of Bank of England) decreased by 1% while it increased by 13% on average for properties located in the periphery.

Next, I estimate a hedonic pricing schedule and assess whether there have been changes to the size premium and commuting penalty in the aftermath of the WFH revolution. I find that, just as in the model, there is a steepening of the size gradient. For example, moving from a $86m^2$ house (i.e. the average size house) to a $102m^2$ house (i.e. the 75th percentile) has a size premium of £79,000 before February 2020 and £83,000 after. The size premium has increased by 5%. Additionally, the penalty associated with being further away from the city centre has decreased. There is a flattening of the distance gradient. The distance penalty associated with the average house in the suburbs relative to the centre was £107,000 before the rise in WFH and £100,000 after. The distance penalty has decreased by 6%.

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

The remainder of the chapter is structured as follows. Section 3.2 presents the data. Section 3.3 shows some raw empirical evidence for changes in London house prices across different dwelling size and distance to the city center. Finally, the hedonic pricing schedule analysis is found in Section 3.4. Section 3.5 concludes.

3.2 Data

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

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

These two data sources provide detailed prices and rents associated with the exact address of the properties. However, information on the dwellings' characteristics is sparse. To bridge this gap I merge the Land Registry and the WhenFresh/Zoopla data with the Energy Performance Certificates dataset that contains a rich set of dwelling characteristics including exact address, type of property, size in square meters, number of rooms, energy rating, energy efficiency, or even window glazing. Since September 2008, properties need to have a valid EPC to be sold or let.[1] Therefore every land registry transaction and every Zoopla rental listing is associated with an EPC. The merging procedure follows Koster and Pinchbeck' s algorithm.[2]

3.3 Size and Distance to the City Center: Evidence from Raw Data

This section starts by presenting some raw data on changes in London's real estate market since 2018. I am interested in analysing the effect of the rise in remote work on house prices and rents. Remote work was very rare before March 2020 and soared at the onset of Covid-19. This change, however, went far beyond the period of the pandemic, and the shift to remote work is highly persistent. For instance in the UK, the ONS reports that 44% of the workforce still worked from home at least one day a week between September 2022 and January 2023. Similarly, Bloom and coauthors (2023) find that in the UK, around 20% of the flow of new jobs allow for at least one day of WFH a week in 2023.[3] Consequently, in the empirical section, I think of March 2020 (the onset of Covid-19) as the start of the rise in WFH.

In the empirical analysis, the geographical unit of observation is London's Travel To Work Area (TTWA). In the UK, TTWAs approximate self-contained labour markets. These are areas where most people both live and work implying that there are relatively few work commutes across TTWAs. These units are based on statistical analysis rather than administrative boundaries.[4] London's

[1] An EPC is valid for 10 years.

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

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

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

TTWA includes all areas within the boundary of Greater London, as well as some local authorities further out that are well connect to central London.

Table 3.1 provides some descriptive statistics from the merged housing dataset. The considered sample is from 2018 to 2021 for rents[5] and from January 2018 to June 2022 for house prices. There is a delay for the Land Registry to officially register a property transaction. This delay - referred to as the "registration gap" by British real estate lawyers - used to be six to eight months, and has been increasing since the Covid pandemic. For this reason, I restrict the analysis to transactions that occurred before 31st of June 2022. Still, I expect that not all the transactions that occurred in the first half of 2022 have been officially registered yet. This explains the relatively low number of observations for the first six months of 2022 compared to the previous years. Table 3.1 reports the number of registered property transactions, the number of rental properties listed on Zoopla, as well as the average transaction price, weekly rent, and property size (in square meters). The number of transactions highlights that, after slowing down during the eye of the pandemic (2020), the real estate sale market was particularly dynamic in 2021.[6] We can also note an increase in the average price and average size of properties sold in London over the sample period. On the other hand, the number of observations for rental listings indicates a post Covid slowing down that persists throughout 2021. Between 2018 and 2021, the average weekly rent is stable, and the average size decreases slightly.

Appreciation of suburban properties: Figure 3.1 displays changes in house prices (panel a), and rents (panel b) as a function of distance to the city center. More precisely, each dot represents one of London's local authority (e.g. Camden, Hackney). The x-axis plots changes in average house prices and rents in each local authority between the year before Covid, and the last year of data available (July 2021 to June 2022 for house prices, and January to December

[5]The Zoopla/Whenfresh data are available until end of 2021.

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

Table 3.1. Descriptive Statistics (London)

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

2021 for rents). The y-axis plots the logarithm of each local authority's average distance to the city center (in meters). Here, I assume that the center of London is Bank of England. A red fitted line is added to the plots.

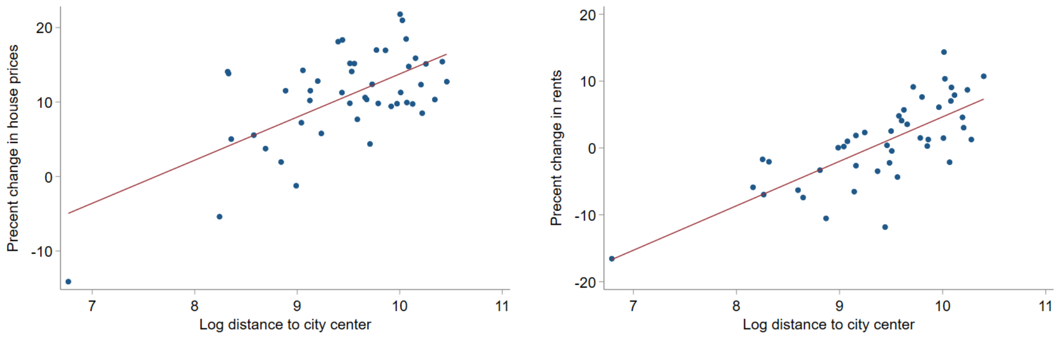
The two figures show a clear positive relationship between real estate appreciation and distance to the city center. In each panel, the outlier point at the bottom left corner is the City of London local authority. This is by far the smallest (and the most central) local authority, and records a drop of around 15% in house prices and rents over the period studied.[7] As an additional test, I produce the same graphs plotting changes in house prices and rents between 2017 and 2018 on the log distance to the city center (the figures can be found in Appendix A). These placebo tests show no positive relationship between properties' appreciation and distance to Bank of England.

The finding that properties located further out appreciated faster since the pandemic and the rise in remote work is not London specific. Bloom and Ramani (2021) document a similar phenomenon for the 12 largest US metropolitan areas. The authors draw the link with working from home, and call this result the *Donut Effect*, referring to the hollowing out of the city centers and the rise in demand for peripheries.

Appreciation of larger properties: After location, I now look at another characteristic relevant to working-from-home: properties' sizes. Figure 3.2 dis-

[7]For robustness, I do the same exercise grouping the City of London local authority together with Westminster in Appendix Figure A.1. The plots look similar as the main text specification.

Figure 3.1. Growth in Prices as a Function of Distance to the Center (London)



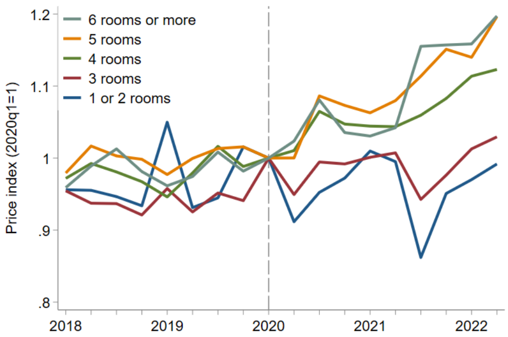
(a) House Prices (b) Rents

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

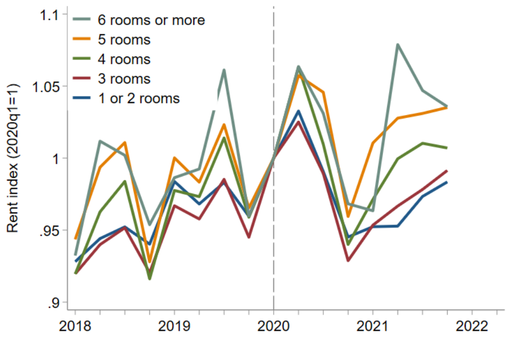
plays house price (panel a), and rent indexes (panel b) by property size. The reference period is February 2020, right before the onset of the pandemic. Properties are split according to their number of rooms.[8] These evidence indicate that larger properties appreciated faster since the rise in remote work. For instance, between February 2020 and June 2022, the average price of large houses (5 rooms or more) increased by 20%, while that of small ones (studio or 1 room) dropped by 1%. Over the same period, rents of large properties (5 rooms or more) grew by 3%, and rents of small houses (studio or 1 room) dropped by 2%.

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

Figure 3.2. House Prices and Rent by Size of Property (London)



(a) House Price Index



(b) Rent Index

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

3.4 Hedonic Pricing Schedule

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

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

$$ln(p_{ijt}) = \delta_P^{size}\ Post\ ln(size_i) + \delta_P^{dist}\ Post\ ln(dist_i) + \delta^{size} ln(size_i) + \delta^{dist} ln(dist_i) + \beta X_i + \alpha_t + \eta_j + e_{ijt} \quad (3.1)$$

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

Table 3.2 reports the estimates of the impact of the log of size and the log of distance to the city center in determining the log of house prices (columns 1 and 3) and the log of rents (columns 2 and 4). Columns 1 and 2 correspond to the specification described above, while columns 3 and 4 conduct a placebo-type test. In these columns, I use data between January 2017 and December 2018. I take the year 2017 as pre-Covid, and 2018 as post-Covid. I expect the interaction term coefficients to be insignificant.

The coefficients associated with $log(size)$ are positive, implying that larger properties have higher prices and rents. These estimates can be interpreted as the percentage change in price or rent for a 1% larger property. For instance, Column 1 indicates that a property that is 1% larger will be 0.723% pricier. The coefficients associated with distance, on the other hand, are negative as properties further away from the city center tend to be cheaper. Column 1's $log(dist)$ coefficient indicates that if a property is 1% further away from the center, its price will be 0.258% lower. The distance gradient is negative.

The third coefficients of Table 3.2 show the interaction effects between size of property and the post Covid-19 period. It indicates how the importance of size in determining house prices and rents changed since the pandemic. In

[9] Available for house prices only.

columns 1 and 2, these coefficients are positive meaning that size became even more important for house prices and rents than it was before the rise of working-from-home. Column 1 indicates that 1% of additional space increases properties' prices by 0.039% more since Covid. Another way to phrase it is that moving from a $86m^2$ house (i.e. the average size house in 2019) to a $102m^2$ house (i.e. the 75th percentile in 2019) has a size premium of £79,000 before February 2020 and £83,000 after. The size premium has increased by 5%. The positive interaction coefficients indicate a steepening of the size gradient. The premium for space increased in the post-pandemic period.

In the non placebo specification, the interaction coefficients between post Covid and distance are negative. The penalty associated with properties located away from the city center decreased. Column 1 reports that being 1% further away from the city center decreases the properties' prices by 0.017% less in the later part of the sample compared to before February 2020. In other words, the distance penalty associated with the average house in the suburbs[10] relative to the centre[11] was £107,000 before the rise in WFH and £100,000 after. The commuting penalty has decreased by 6%. This indicates a flattening of the distance gradient. This result is in line with evidence from the US in which Gupta, et al. (2021) report a similar flattening of the distance gradient. We note that all the size and distance coefficients of columns 1 and 2 are statistically significant for house prices as well as for rents.

Finally, the interaction coefficients of the placebo specifications in columns 3 and 4 are not statistically significant. Some robustness exercises including using a dummy for number of rooms instead of size in square meters, adding an interaction between size and distance, and using a two-way-fixed-effect can be found in Appendix C. These results are similar to the baseline specification. Appendix D presents the results of an alternative specification, where I let the

[10]The area qualified as "Outer London" by the ONS. It is roughly the area beyond zones 1 and 2 of the London underground.

[11]The area qualified as "Inner London" by the ONS. It roughly corresponds to zones 1 and 2 of the London underground.

size and distance coefficients vary every month. The results also show a drop in commuting penalty and an increase in the premium for space.

Table 3.2. Impact of Size and Distance to City Center on House Prices and Rents

	(1) log_price	(2) log_rent	(3) log_price	(4) log_rent
log_size	0.723***	0.532***	0.680***	0.536***
log_dist	-0.258***	-0.180***	-0.291***	-0.185***
log_size after WFH	0.039***	0.026***	0.012	-0.003
log_dist after WFH	0.017*	0.047***	0.007	0.000
N	468,137	416,530	432,077	433,459
adj. R^2	0.581	0.658	0.566	0.662
Placebo	NO	NO	YES	YES
Monthly FE	YES	YES	YES	YES
LA FE	YES	YES	YES	YES
Property controls	YES	YES	YES	YES
SE	Clust. at LA	Clust. at LA	Clust. at LA	Clust. at LA

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

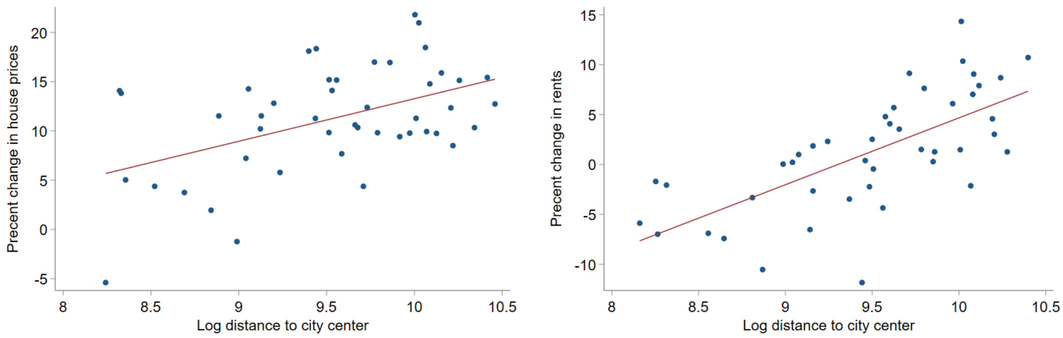
3.5 Conclusion

This chapter provides novel empirical evidence on London house prices and rents. Using detailed property-level data, I show that larger properties and properties located away from the city center appreciated the most since the rise in remote work. The rich data is then explored in a hedonic pricing schedule to assess whether there have been changes to the size premium and commuting penalty in the aftermath of the WFH revolution. I find evidence for a 5% rise in the premium for space and a 6% decline in the commuting penalty. However, in its current state, this study does not establish a direct link between the reported price changes and remote work. An interesting extension would be to establish this direct link by constructing a neighbourhood-specific measure of WFH exposure prior to the pandemic. The WFH exposure could be constructed using the occupation split of residents at the local authority level and the very detailed UK job vacancy data from Hansen, Lambert, Bloom, Davis, Sadun and Taska (2023), which provides information on the share of vacancies that explicitly allow workers to work remotely by 4-digit occupation code.

3.A Appendix A: Raw Data - Prices and Distance to the City Center

Figure A.1 reproduces the plots in Figure 3.1 grouping together the local authorities of the City of London and Westminster. The plots look similar to the ones in the main text specification.

Appendix Figure A.1. Growth in Prices as a Function of Distance to the Center (London - Grouping City of London with Westminster)



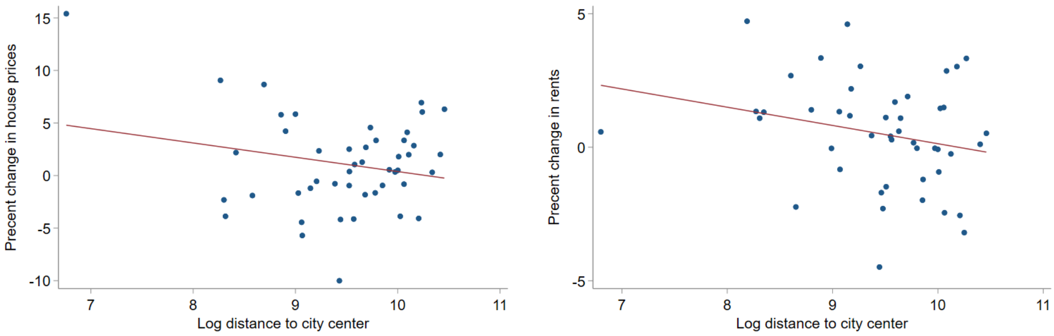
(a) House Prices (b) Rents

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

Figure A.2 reproduces the plots in Figure 3.1 for a placebo period. I plot changes in house prices and rents between 2017 and 2018 on local authorities' average log distance to the city center. In this placebo specification, we do not observe the clear positive relationship emphasized during the Covid period.

Figure A.3 provides additional evidence for the relative appreciation of properties located further out from the city center. The left panels plot house price indexes and the right panels plot rent indexes. The reference period is February 2020. In the top two panels, properties are split into two groups: the center

Appendix Figure A.2. Growth in Prices as a Function of Distance to the Center (London - Placebo)



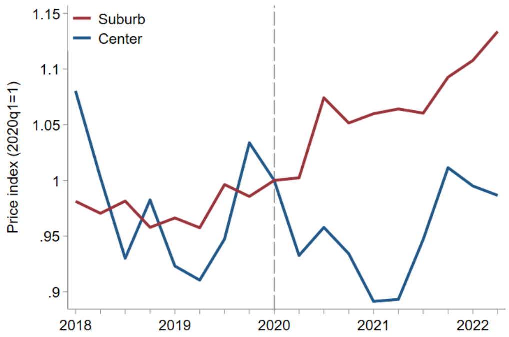
(a) House Prices

(b) Rents

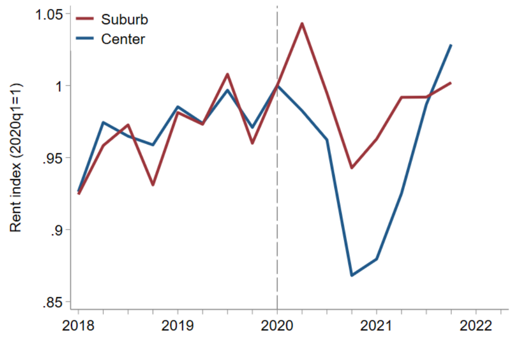
Notes: Each dot represents one of London's local authority (e.g. Camden, Hackney). As this is the placebo specification, the x-axis plots changes in average house prices and rents between the year 2017 and 2018. The y-axis plots the logarithm of local authority's average distance to Bank of England (in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

properties that are within a 5km radius of BoE and the suburban properties that are located further out. In the bottom two panels, I plot properties by quintile of distance to the city center. In both specifications, since February 2020, properties located further away from the city center appreciated faster than more central ones.

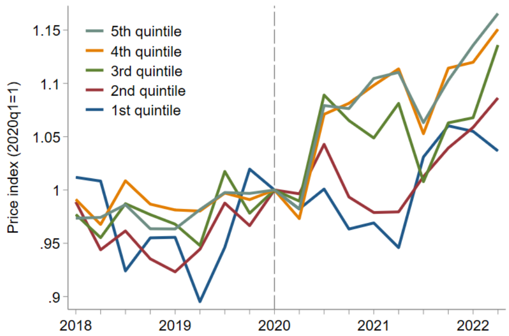
Appendix Figure A.3. House Prices and Rents by Distance to the City Center (London)



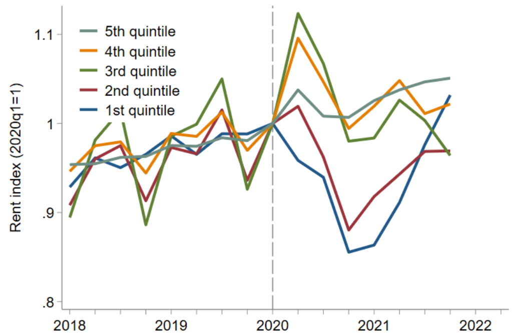
(a) House Price Index (Center/Suburb)



(b) Rent Index (Center/Suburb)



(c) House Price Index (Distance Quintiles)



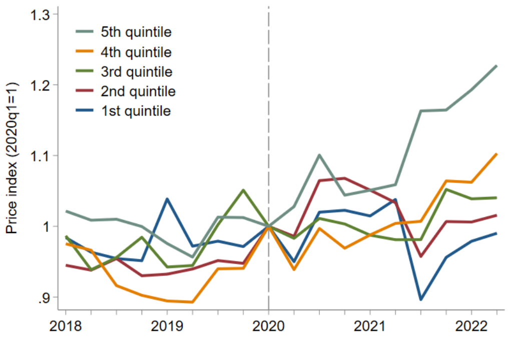
(d) Rent Index (Distance Quintiles)

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

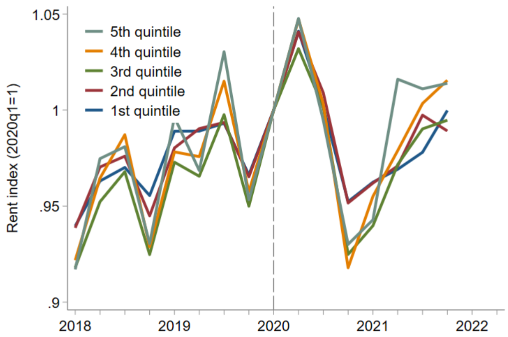
3.B Appendix B: Raw Data - Prices and Size

Figure B.1 reproduces the evidence displayed in Figure 3.2 - the relative appreciation of larger properties since February 2020 - splitting the data by quitile of size in m^2 (instead of by number of rooms). This plot is similar to the alternative specification of the main text.

Appendix Figure B.1. House Prices and Rent by Size of Property (London)



(a) House Price Index



(b) Rent Index

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

3.C Appendix C: Robustness for Hedonic Specification

Table C.1 provides some robustness checks for the hedonic price schedules estimated in Section 3.4. Columns 1 and 2 use a dummy for large dwelling (larger than three rooms) instead of the logarithm of square meters to capture properties' size. Columns 3 and 4 use a two-way-fixed-effect for month and local authority. Finally, columns 5 and 6 include an interaction term between size and distance to the city center. The results are similar to the baseline specification in the main text.

Appendix Table C.1. Impact of Size and Distance to City Center on House Prices and Rents (Robustness)

	(1) log_price	(2) log_rent	(3) log_price	(4) log_rent	(5) log_price	(6) log_rent
log_size			0.721***	0.531***	0.912***	1.189***
large dummy (+3 rooms)	0.236***	0.251***				
log_dist	-0.243***	-0.184***	-0.278***	-0.183***	-0.171*	0.118
log_dist inter. log_size					-0.020	-0.073**
log_size after WFH			0.042***	0.027***	0.039***	0.021***
large dummy after WFH	0.048***	0.027***				
log_dist after WFH	0.004	0.046***	0.058**	0.057***	0.017*	0.047***
N	384,086	406,791	468,137	416,726	468,137	416,530
adj. R^2	0.476	0.523	0.586	0.660	0.582	0.660
Monthly FE	YES	YES	NO	NO	YES	YES
LA FE	YES	YES	NO	NO	YES	YES
TWFE	NO	NO	YES	YES	NO	NO
Property controls	YES	YES	YES	YES	YES	YES
SE	Clust. at LA	Clust. at LA	Clust. at LA	Clust. at LA	Clust. at LA	Clust. at LA

Notes: * $p < .10$, ** $p < .05$, *** $p < .01$. This Table reports results from OLS regressions of the hedonic price schedules from Section 2 using the log of house prices (columns 1, 3, and 5) and the log of listed rents (columns 2, 4, and 6) as dependent variables. Controls at the property-level: type of property, energy rating, energy efficiency, presence of a fireplace, whether the property is a leasehold, and whether the property is new (for house prices equation only). Inter. stands for interacted. Large dummy is equal to 1 when properties have more than 3 rooms.

3.D Appendix D: Alternative Hedonic Specification (Monthly Coefficients)

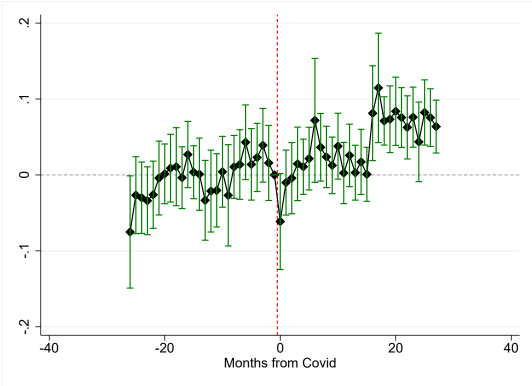
Equation 3.1 in the main text evaluates the total change in the importance of size and distance in determining house prices and rents for the overall post pandemic period. Another interesting exercise is to look at the size and distance gradients in every month of our sample.

$$ln(p_{ijt}) = \delta_t^{size} ln(size_i) + \delta_t^{dist} ln(dist_i) + \beta X_i + \alpha_t + \eta_j + e_{ijt} \tag{3.2}$$

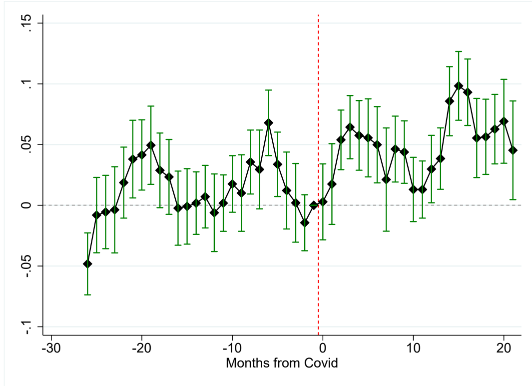
Equation 3.2 allows for the coefficients of log size and log distance to vary every month. They capture the effect of size and distance on the outcome variable in each month relative to the default period of February 2020. These month-specific coefficients allow to test for pre-trends.

Figure D.1 plots the size and distance monthly coefficients from Equation 3.2. The top 2 panels display δ_t^{size} for house prices (Panel a) and rents (Panel

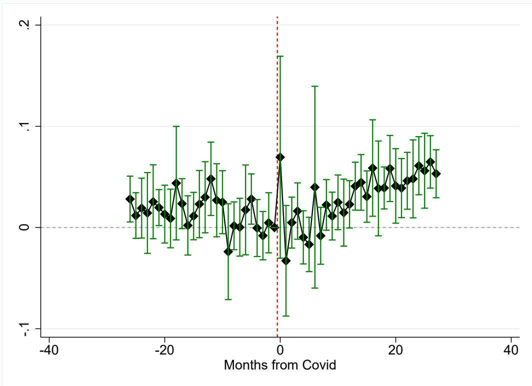
Appendix Figure D.1. Month-Specific Size and Distance Coefficients (London)



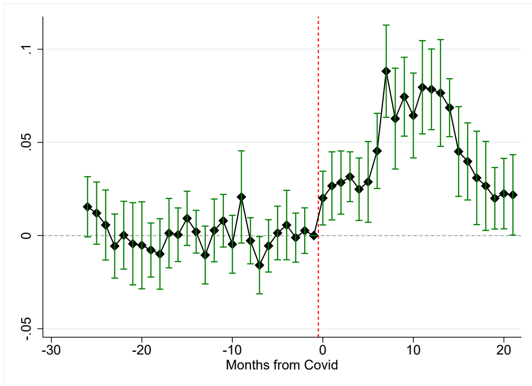
(a) Size Coefficients on House Prices



(b) Size Coefficients on Rents



(c) Distance Coefficients on House Prices



(d) Distance Coefficients on Rents

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

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

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