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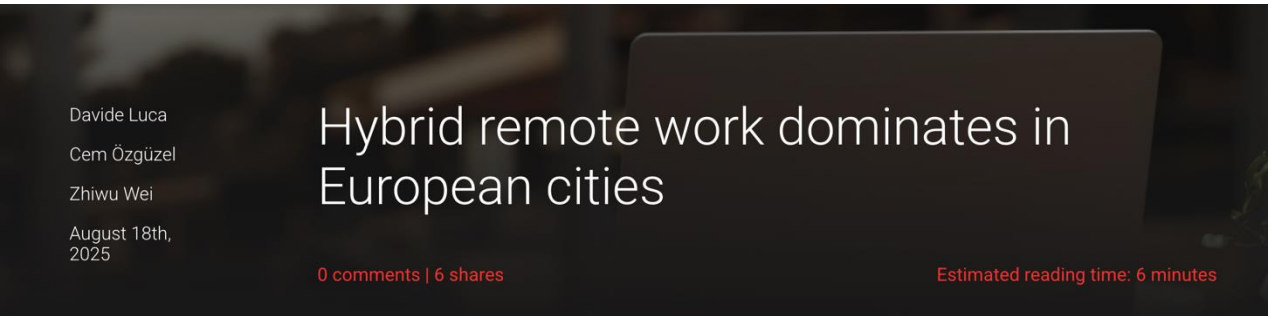
Beyond The City

Remote Working and Residential Relocations in The UK

Conor O'Driscoll and Federica Rossi

27-08-2025, ERSA, Athens, Greece

Motivation and Theoretical Background



The new geography of remote jobs in Europe

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ABSTRACT

The paper maps the diffusion of working from home across 30 European countries during the COVID-19 pandemic. We summarise the determinants of remote working and show that its uptake was lower than in the United States, and substantially uneven across/within countries, with most remote jobs concentrated in cities and capital regions. We then apply a variance decomposition procedure to investigate whether the uneven distribution of remote jobs can be attributed to individual or territorial factors. Results underscore the importance of composition effects as, compared with intermediate-density and rural areas, cities hosted more workers in occupations/sectors more amenable to working remotely.

KEYWORDS
work from home; remote work; telework; COVID-19; Europe

JEL I18, J20, O52, P25
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The Geography of Remote Work☆

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ABSTRACT

High-income business service workers dominate the economies of major US cities, and their spending supports many local consumer service jobs. As a result, business services' high remote work potential poses a risk to consumer service workers who could lose an essential source of revenue if business service workers left big cities to work from elsewhere. We use the COVID-19-induced increase in remote work to provide empirical evidence for this mechanism and its role in shaping the pandemic's economic impact. Our findings have broader implications for the distributional consequences of the transition to more remote work.

Intercity impacts of work-from-home with both remote and non-remote workers

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ABSTRACT

This paper generalizes the simple two-city work-from-home model of Brueckner et al. (2022) by adding a group of non-remote workers, who must live in the city where they work. The results show that the main qualitative conclusions of BKL regarding the intercity effects of WFH are unaffected by this modification, with WFH yielding the same aggregate population and employment changes in the two cities and the same house-price and wage effects as in the simpler model. Even though the aggregate population effects are the same, the population relocation of non-remote workers is in the opposite direction to that of remote workers, which matches the direction in BKL. These conclusions are useful because they establish the robustness of BKL's highly parsimonious model. The paper also contains material surveying other theoretical research on WFH as well as empirical work in the area, including BKL's empirical findings in support of their model.

Cnossen & Koster (2024)

Shadows and Donuts: The Work-From-Home Revolution and The Performance of Cities

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Keywords: agglomeration economies | commuting frequency | labour markets | labour mobility | working-from-home

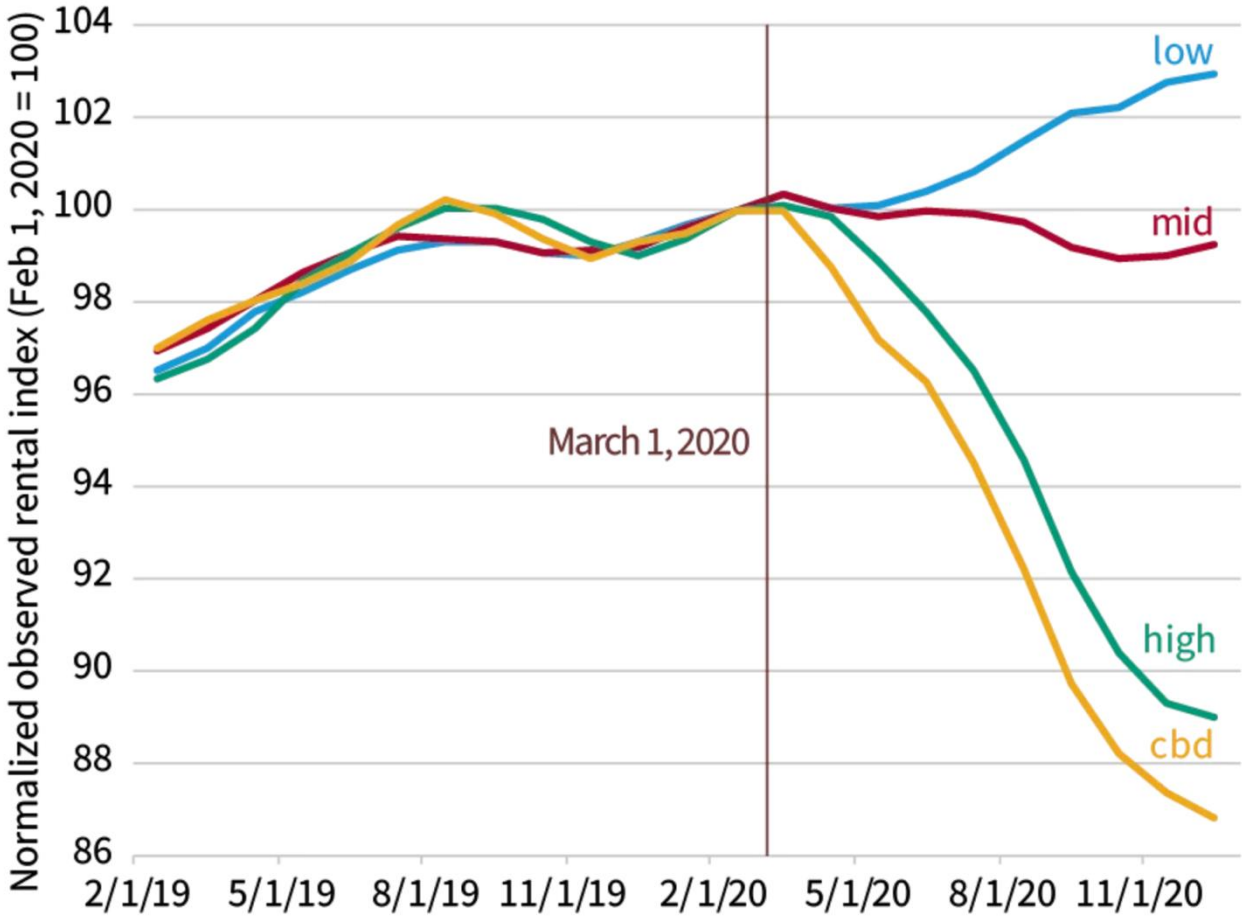
ABSTRACT

In this article, we set out the relationships between the behavioral and spatial responses to working from home. The analytical framework centres explicitly on the choice of commuting frequency as the key decision-making variable that endogenously reshapes the relationships between other spatial and nonspatial variables as a result of the work-from-home revolution. We find that optimal commuting frequency is positively related to the opportunity costs of less-than-continuous face-to-face interaction and inversely related to commuting costs. As well as a " donut effect" with growth in the suburbs and hinterlands around cities, our results also identify a "shadow effect" in smaller cities. The reason is that, somewhat counterintuitively, commuting frequency optimisation magnifies the benefits of working from home in larger cities because of a greater decrease in the burden of commuting. Our results imply enhanced productivity of larger cities over smaller cities, suggesting that the economic divergence between large cities and left-behind places is likely to persist.

JEL Classification: D24, E24, J24, J61, R12, R23

O'Driscoll and Rossi (2025)

Fig 1: Normalized Zillow observed rental index broken down by density group and CBD for 12 largest metros by population (Feb 1, 2020 = 100)



Theoretical Background

- **Urban/Regional Economics** (i.e., Rosen-Roback and Bid-Rent):
  - Individuals and firms choose locations based on trade-offs between wages, rents, and amenities. WFH alters this equilibrium by decoupling job and residential locations.
- Determinants of **Internal Migration**
  - Migration decisions are influenced by employment, housing, family, and life-course factors. WFH introduces a new driver: flexibility in job location decoupled from residence.
- **Agglomeration Economies**
  - Urban density supports productivity, knowledge spillovers, and innovation. Remote work may erode these benefits or shift agglomeration from physical to digital spaces.

O'Driscoll and Rossi (2025)

Where Are We Then?

- To what extent does WFH impact the the decision to relocate?
  - **SPOILER:** A small bit; not as much now as it did during COVID.

- To what extent does WFH impact the destination people relocate to?
  - **SPOILER:** Positively associated with suburbanization, if anything. But no clear evidence that this is shaped by rural/urban out-migration.

O'Driscol and Rossil (2025)

Design, Data, and Definitions

The Strategy

- **Stage 1:** Does WFH impact the probability of relocating?
  - Binary Indicator: Moved address since previous survey wave.

- **Stage 2:** Does WFH impact the destinations individuals move to?
  - Nominal Indicator: Moved to i) City, ii) Suburb or Independent Town, iii) Rural or Peripheral Area.

- **Main Independent Variable:** WFH “Frequently” * Year Dummies.

O’Driscoll and Rossi (2025)

Measuring WFH Frequently

- A dummy indicator constructed from three survey items:
  1. Main workplace location (i.e., home, employer's premises, mobile);
  2. Does employer offer WFH arrangements (yes/no);
  3. Does individual regularly engage in WFH (yes/no).

- Definition of "Regular" and "Frequently" left up to the discretion of the interviewer and interviewee.
  - Hybrid Work Arrangements = Fully Remote?

O'Driscoll and Rossi (2025)

The Method: First-Stage

- Mixed-Effects Binary Logistic Regression.
  - Random individual-level intercepts (α_i) and Region (γ_r) and Year (δ_t) Fixed-Effects.
  - Individual-level socio-demographic controls ($\boldsymbol{x}_{it}^{\top}\beta$).

$$logit\big(P(y_{it}=1)\big) = \boldsymbol{x}_{it}^{\top}\beta + WFH_{it} * \delta_t + \alpha_i + \gamma_r + \varepsilon_{it}$$

- Fixed-Effects Binary Logistic Regression and Linear Probability Models used for robustness checks.

O'Driscoll and Rossi (2025)

The Method: Second-Stage

- Mixed-Effects Multinomial Logistic Regression.
  - Random individual-level intercepts (α_i) and Region (γ_r) and Year (δ_t) Fixed-Effects.
  - Individual-level socio-demographic controls ($\boldsymbol{x}_{it}^{\top}\beta$).
  - Alternative-specific covariates ($\boldsymbol{z}_{it}^{\top}\theta_j$).

$$P_{ijt} = \frac{\exp(\boldsymbol{x}_{ijt}^{\top}\beta + \boldsymbol{z}_{it}^{\top}\theta_j + WFH_{it} * \delta_t + \alpha_i + \gamma_r)}{\sum_{j=1}^{J} \exp(\boldsymbol{x}_{ijt}^{\top}\beta + \boldsymbol{z}_{it}^{\top}\theta_j + WFH_{it} * \delta_t + \alpha_i + \gamma_r)}$$

- Mixed-Effects Binary Logistic Regression and Linear Probability Models used for robustness checks.

UK Household Longitudinal Survey (2019-2023)

- *UKHLS* captures a range of social, economic and attitudinal information about the lives of (all) members of 40,000 households through an annual, computer-assisted, personal interview.
- Individual-level panel data (2019-2023) geocoded at the Lower Layer Super Output Area level.
  - 2,597 individuals for the first stage and 577 retained for the second stage.

O'Driscoll and Rossi (2025)

Spatial Data

- *Torres and McArthur (2024)* compute spatial accessibility indicators at the LSOA level (i.e., distance to nearest city, share of employment opportunities accessible within 15 minutes).
- *Fleischmann and Arribas-Bel (2022)* compute spatial signatures (i.e., geographical characterisations of urban form) across the UK at LSOA level.
  - This dataset allows me to compute a measure of land-use mixing, but it also allows me to document the predominant land-use class in a given area.
- *Ballantyne and Beragen (2024)* count the number (and type) of points-of-interest across the UK at the LSOA level.

Results, Discussion, and Conclusion

Baseline Estimates: Aggregate Trends

Table 3: Locational Mobility and WFH Arrangements

	LPM	Mixed Logit	FE Logit
WFH Frequently	0.006	1.215+	1.284
	(0.008)	(0.124)	(0.268)
Robust Standard Errors	Yes	No	Yes
Year Fixed Effects	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes
Num.Obs.	12985	12985	2880
R2	0.019	0.059	0.081
AIC	-5624.0	5098.0	4135.2
BIC	-5429.7	5299.7	7720.5
RMSE	0.19	0.21	0.41

+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001

The coefficients presented in the Mixed and FE Logit estimators are exponentiated, representing odds ratios.

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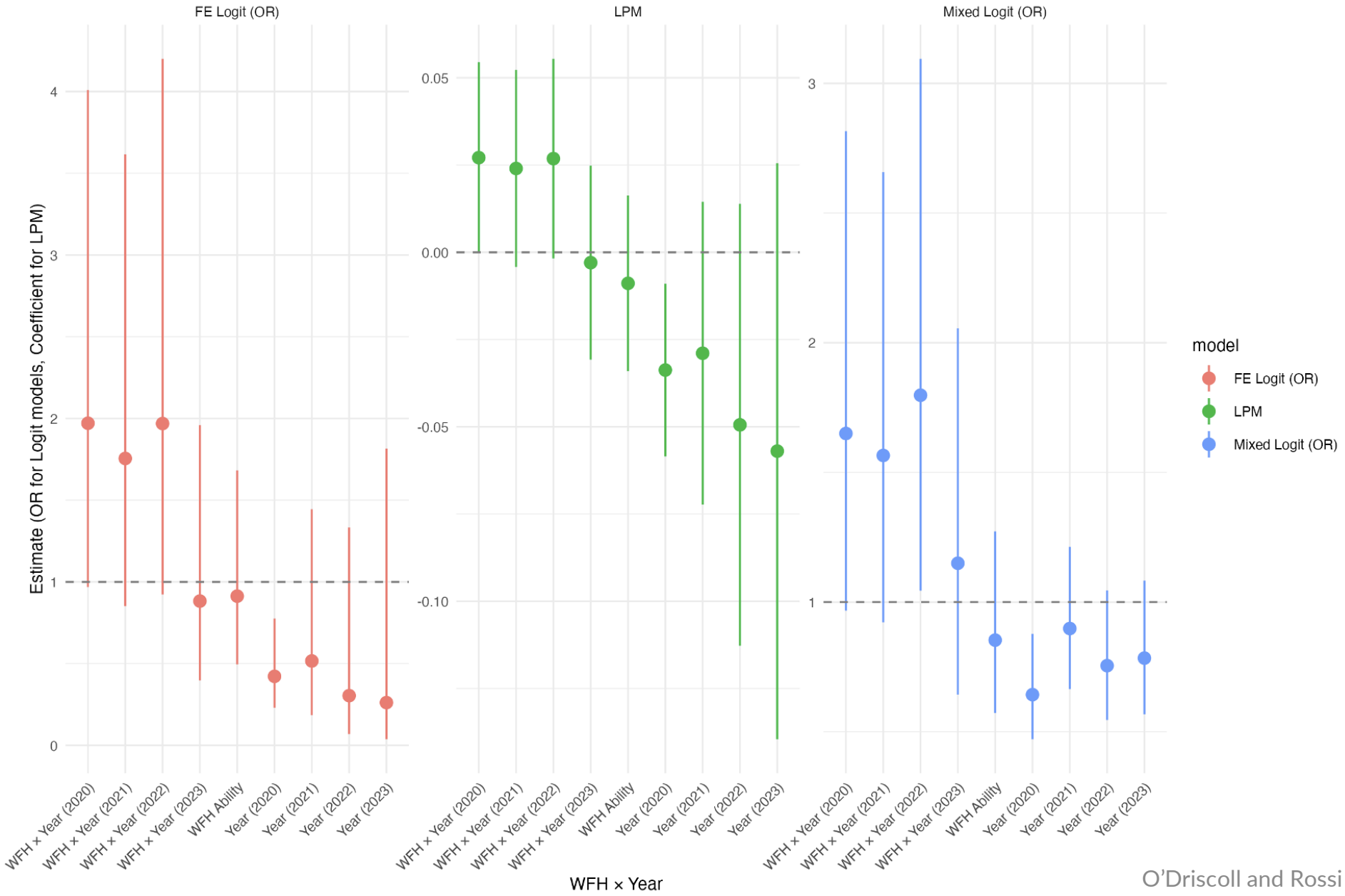

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Table 4: Destination-Specific Heterogeneity in Locational Mobility

	Linear Probability Models			Mixed-Effects Binary Logistic Regression		
	Move To City	**Move To Suburb**	**Move To Rural**	**Move To City**	**Move To Suburb**	**Move To Rural**
WFH Frequently	0.018	-0.037	-0.002	1.459	0.801	0.659
	(0.018)	(0.045)	(0.025)	(0.655)	(0.203)	(0.336)
Year (2020)	-0.045**	-0.077+	-0.025	0.171*	0.597**	0.911
	(0.017)	(0.044)	(0.024)	(0.131)	(0.117)	(0.292)
Year (2021)	-0.051+	-0.041	-0.024	0.589	0.768	1.278
	(0.029)	(0.074)	(0.041)	(0.300)	(0.148)	(0.388)
Year (2022)	-0.069+	-0.065	-0.069	0.678	0.596*	0.782
	(0.041)	(0.105)	(0.058)	(0.345)	(0.124)	(0.269)
Year (2023)	-0.084	-0.030	-0.116	0.620	0.749	0.393*
	(0.054)	(0.137)	(0.075)	(0.317)	(0.147)	(0.165)
WFH Frequently x Year (2020)	0.002	0.105*	0.003	2.867	1.857+	0.991
	(0.020)	(0.052)	(0.028)	(2.635)	(0.628)	(0.661)
WFH Frequently x Year (2021)	0.002	0.079	0.011	1.117	1.590	1.302
	(0.021)	(0.054)	(0.030)	(0.796)	(0.542)	(0.814)
WFH Frequently x Year (2022)	-0.033	0.106*	0.035	0.161+	2.092*	1.992
	(0.021)	(0.053)	(0.029)	(0.154)	(0.720)	(1.272)
WFH Frequently x Year (2023)	-0.022	-0.028	0.052+	0.586	0.840	3.000
	(0.021)	(0.055)	(0.030)	(0.459)	(0.308)	(2.124)
Robust Standard Errors	Yes	Yes	Yes	No	No	No
Region Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes
Num.Obs.	2885	2885	2885	2885	2885	2885
R2	0.025	0.031	0.046	NA	NA	NA
R2 Marg.	NA	NA	NA	0.347	0.050	0.289
AIC	-3283.1	2124.1	-1344.9	607.0	2613.9	1111.2
BIC	-3104.1	2303.1	-1165.9	791.9	2798.9	1296.2
RMSE	0.14	0.35	0.19	0.15	0.37	0.21

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

LPM models report marginal effects. Logit models report odds ratios.

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Table 5: Multinomial Logistic Regression Results For Relocation Destinations

	City	Suburb	Rural
WFH Frequently x Year (2020)	3.222	1.934+	1.113
	(3.055)	(0.665)	(0.750)
WFH Frequently x Year (2021)	1.216	1.648	1.485
	(0.910)	(0.571)	(0.938)
WFH Frequently x Year (2022)	0.154+	2.161*	2.271
	(0.154)	(0.755)	(1.465)
WFH Frequently x Year (2023)	0.667	0.844	2.801
	(0.541)	(0.314)	(2.000)
WFH	1.185	[illegible]	0.671
	(0.563)	[illegible]	(0.346)
Year (2020)	0.151*	0.561**	0.780
	(0.117)	(0.111)	(0.252)
Year (2021)	0.686	0.757	1.095
	(0.357)	(0.148)	(0.338)
Year (2022)	0.702	0.562**	0.646
	(0.365)	(0.118)	(0.225)
Year (2023)	0.652	0.695+	0.338*
	(0.344)	(0.138)	(0.143)
Region Fixed Effects	Yes		
Individual Controls	Yes		
Num.Obs	2885		
Log Likelihood	-1972.2727		
Wald-Chi2	301.98***		
AIC	4132.545		
BIC	4693.47		
Pseudo R^2	0.092		
Brier Score	0.095		

+ $p < 0.1$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. The coefficients reported are odds ratios and default standard errors are used. The reference category is "Did not move in a given year, but did in some other year".

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What Does This Mean?

- Average effects show no significant link between working-from-home frequently and locational mobility, but this masks divergent trends.
  - Individuals unable to WFH experienced reduced mobility (particularly in 2020), marked by lower odds of relocating to cities or suburbs.
  - Frequent remote workers became more mobile, especially toward suburban areas, reflecting increased spatial flexibility and lifestyle re-evaluation.

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WFH: A Form of Mobility Capital?

- WFH provides greater freedom to optimise lifestyle and housing choices.
- Those tied to in-person jobs face constraints in relocating or accessing better neighbourhoods.
- WFH capacity acts as a sorting mechanism, reinforcing social and spatial inequalities.

O'Driscoll and Rossi (2025)

Thank you!

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Statistic	N	Mean	St. Dev.	Min	Max
Sex (1 = Male)	12,985	0.47	0.50	0	1
Age	12,985	46.94	9.59	25	65
Nonwhite (1 = Yes)	12,985	0.18	0.39	0	1
University Educated (1 = Yes)	12,985	0.58	0.49	0	1
Changed Marital Status Since Previous Year (1 = Yes)	12,985	0.04	0.20	0	1
Had Kids Since Previous Year (1 = Yes)	12,985	0.02	0.14	0	1
Changed Employer Since Previous Year (1 = Yes)	12,985	0.15	0.35	0	1
Owns A Car (1 = Yes)	12,985	0.89	0.31	0	1
Net Monthly Individual Income	12,985	2,340.46	2,011.52	0.08	87,257.08
Works in a Management/Professional Occupation (1 = Yes)	12,985	0.48	0.50	0	1
Works in an Intermediate Occupation (1 = Yes)	12,985	0.21	0.40	0	1
Works in a (Semi-)Routine Occupation (1 = Yes)	12,985	0.32	0.47	0	1
Minutes Spent Travelling To Work	12,985	18.92	21.03	0	180
Works-from-home frequently (1 = Yes)	12,985	0.36	0.48	0	1
Relocated to a new address Since Previous Year (1 = Yes)	12,985	0.05	0.23	0	1

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Statistic	N	Mean	St. Dev.	Min	Max
Sex (1 = Male)	2,885	0.48	0.50	0	1
Age	2,885	41.70	10.17	25	65
Nonwhite (1 = Yes)	2,885	0.16	0.36	0	1
University Educated (1 = Yes)	2,885	0.66	0.47	0	1
Changed Marital Status Since Previous Year (1 = Yes)	2,885	0.07	0.26	0	1
Had Kids Since Previous Year (1 = Yes)	2,885	0.04	0.20	0	1
Changed Employer Since Previous Year (1 = Yes)	2,885	0.19	0.39	0	1
Owns A Car (1 = Yes)	2,885	0.88	0.33	0	1
Net Monthly Individual Income	2,885	2,490.23	1,995.63	1.00	51,671.56
Works in a Management/Professional Occupation (1 = Yes)	2,885	0.55	0.50	0	1
Works in an Intermediate Occupation (1 = Yes)	2,885	0.17	0.37	0	1
Works in a (Semi-)Routine Occupation (1 = Yes)	2,885	0.29	0.45	0	1
Minutes Spent Travelling To Work	2,885	20.00	22.38	0	180
Works-from-home frequently (1 = Yes)	2,885	0.41	0.49	0	1
Relocated to a new address Since Previous Year (1 = Yes)	2,885	0.24	0.43	0	1
LSOA Proportion of Employment Opportunities Within 30 Minutes[1]	2,885	2.47	3.00	0.02	19.52
LSOA Land-Use Mixing[2]	2,885	0.20	0.13	0.00	0.62
LSOA Total Amenity/POI Count[3]	2,885	68.75	95.08	2	1,999
LSOA Distance To Nearest City[1]	2,885	12.74	6.78	0	60

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