Which amenities make remote workers take longer commutes? An empirical assessment upon Spanish data

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ABSTRACT. The rise of working from home (WFH) is arguably one of the most notable effects derived from the digital transition. It is also a viable channel to tackle rural depopulation, for it enables employees to live further away from their workplaces as they have to commute less times per week, if any. In this paper, we hypothesise that not all non-urban places are as attractive for remote workers. Our aim is to study which amenities make non-urban areas attractive enough for remote workers to take longer commuting distances. We predicate a regression model relating commuting distances to WFH probabilities and a limited set of amenities using Spanish 2021 Census microdata. Accessibility to private services, such as restaurants or supermarkets does not show significant interaction effects with WFH probabilities in explaining longer commutes. But individuals with higher WFH probabilities and accessibility to schools do seem to place themselves further away from their workplaces.

KEY WORDS: digital transition; local attractiveness; commuting distance; urban sprawl

JEL CODES: J61; R11; R23

1. Introduction

European working population is concentrating in urban areas, while shrinking in rural areas (Goujon et al., 2021). Between 2014 and 2024, the share of employed population residing in the EU-27 rural areas declined by 57% (figure 1). The depopulation of non-urban areas has become a first-order issue in the European Union´s (EU) regional policy since it correlates with political discontent (Rodríguez-Pose, 2018) as well as with a poorer conservation of the cultural heritage and the environment (Pedroli, Pinto Correia & Primdahl, 2016). At least in some EU territories, depopulation seems to be driven by a "vicious circle" that starts with the migration of young cohorts due to relative economic decline. Consequently, birth rates drop, thus reinforcing social and economic stagnation (García Marín & Espejo Marín, 2019).

[FIGURE 1 AROUND HERE]

Figure 1. Percentage changes in the shares of employment for urban, intermediate and rural areas in the EU27, 2014-2024.
Source: own elaboration.

As a response, improving the digital connectivity of non-urban areas is one of the main pillars in the European Union´s (EU) *Long term vision for rural areas* (European Commission, 2021) to rebalance population across space. The spread of remote work after the Covid-19 pandemic is one of the main channels through which the digital transition can contribute to alleviate depopulation in some non-urban areas. This is because, despite not being a unique solution, it may offer opportunities for at least some jobs to be done from anywhere (Barzotto et al., 2025).

While a widespread adoption of remote work seems not yet possible (Crescenzi et al., 2022; Florida et al., 2023), some empirical evidence suggests a slow but steady shift towards remote work in some occupations and industries (Dingel & Neiman, 2020). Survey data shows that workers value working from home (WFH) more after the Covid-19 pandemic (Barrero et al., 2021). Furthermore, the productivity of remote work has increased as workers and firms got used to new organisational and technological arrangements (Davis et al., 2024). Consequently, the rise of working from home is arguably one of the most notable effects of the digital transition (Barrero et al., 2023).

Working from home distorts spatial equilibria defining population´s distribution across space by altering the link between the places of residence and work. Partial or total WFH arrangements lower commuting costs, thus enabling additional spatial arbitrage opportunities for individuals (Brueckner et al., 2023; Brueckner & Sayantani, 2023; Delventhal & Parkhomenko, 2024; Lennox, 2020). Therefore, remote workers can choose to live further away from their place of work than do their onsite colleagues. This implies an opportunity for urban sprawl, at least in the United States and Europe, where most jobs that are amenable to be done remotely cluster around cities (Luca et al., 2024; OECD, 2020). Consistent with this finding, empirical data for commuting patterns and real estate prices point to the relationship between remote work and urban sprawl around metropolitan areas (Ahrend et al., 2023; Ramani et al., 2024). The effects of WFH add to other pandemic-related changes in location preferences that increase the size of the area around cities in which people are willing to live (Ramani & Bloom, 2021).

Among the expanded set of possibilities enabled by remote work, which location would an individual choose to live? Using different modelling frameworks, the contributions by Tiebout (1956), Graves & Linneman (1979) and Robak (1982), among others, suggest that spatial equilibria are driven by differences in wages, rents and amenities. Our interest in this paper is on the latter local feature. The empirical literature on local attractiveness shows stronger preferences for amenities by highly educated workers (Diamond, 2016; Niedomysl & Hansen, 2010) and by employees of the Information and Technology (IT) sectors (Song et al., 2016). These findings appear to be consistent with the insights given in the literature on local attractiveness. A number of studies with differing geographical coverages find empirical evidence on the positive role of service, natural and cultural amenities to explain population growth and migration (see Panori et al., 2024 for a recent review).

But, to the best of our knowledge, there is little evidence on whether they are (sets of) amenities that make residential locations further away from workplaces attractive for individuals who can potentially work remotely. We provide further evidence on whether jobs amenable to be done remotely contribute to urban sprawl in Europe on the basis of a large scale survey: the 2021 Census of Spain. We thus extend the work done using smaller, yet much more specific, *ad hoc* surveys (de Abreu e Silva, 2022; Jansen et al., 2024).

2. Conceptual framework

Our identification strategy relies upon the literature on spatial equilibrium models after the contributions of Rosen (1974) and Roback (1982, 1988). Without losing generality, let there be two locations: i, j. In equilibrium, the utility of an individual working and living at location j is given by:

$$u_{jj} = A_j + w_j + q_j - p_j q_j + e_j \tag{1}$$

In equation (1), A_j stands for the access to amenities in location j. Wages at j are given by w_j. Utility relates to the local housing markets in two ways. First, q_j accounts for the dwelling size available. Second, $p_j q_j$ gives the local housing costs. Finally, individuals may have idiosyncratic preferences for a given location (e_j) as in Moretti (2010). Idiosyncratic preferences can correlate with socioeconomic characteristics—e.g.: age, sex, education level, presence of kids; as suggested by So et al., (2001). But they can also be the result of social networks, for instance, the presence of close family.

The utility for an individual choosing to work at location j and live in location i is given by:

$$u_{ij} = A_i + w_j + q_i - p_i q_i + e_i - td_{ij} \tag{2}$$

In equilibrium, the utility derived from the access to amenities, housing size, housing prices and idiosyncratic preferences must compensate for commuting costs (td_{ij}). Commuting costs depend on the distance from i to j (d_{ij}) and the number of commutes (t). We find how do individuals choose their distance between job and residential locations equating (1) and (2) and solving for d_{ij}:

$$d_{ij} = \frac{1}{t}\left[\left(A_i - A_j\right) + \left(q_i - q_j\right) + \left(p_j q_j - p_i q_i\right) + \left(e_i - e_j\right)\right] \quad (3)$$

The distance that an individual chooses to live relative to her workplace positively depend, first, on the amenity, dwelling and price differentials. Second, on her idiosyncratic preferences for one location over the other. And third, negatively on the number of commutes that she takes to her work, for d_{ij} tends to infinite as t approaches zero. Let a tilde (~) denote an alternative equilibrium in which remote work allows for fewer travels to the workplace. As $\tilde{t} < t$, it straightforward follows that $\tilde{d}_{ij} > d_{ij}$. Therefore, we expect remote work and its interactions with the differences in the right-hand side of (3) to have a positive impact on the commuting distances of individuals.

3. Empirical application

3.1. Our study in context

After recovering from the effects of the financial crisis, territorial imbalances became a central policy issue in Spain´s local, regional and national agenda (Federación Española de Municipios y Provincias, 2017). The idea of the "empty/emptied Spain" is now a commonplace both in the literature and among the public (Díez-Gutiérrez & Rodríguez-Rejas, 2021). Llorent-Bedmar, Cobano-Delgado Palma & Navarro Granados (2021) point that the internal migrants' distribution from rural Spain to the cities are skewed towards younger generations due to rural relative economic stagnation and a feeling of inferiority. As a result, birth rates drop and therefore economic and social stagnation is reinforced as in a vicious circle (García Marín & Espejo Marín, 2019).

Gutiérrez et al. (2023) show that the Spanish distribution of population is a historical anomaly in the European context: Spain´s population shows a higher concentration in a low number of settlements. As per Oto-Peralías (2020), they conjecture that the Reconquest process and the subsequent Christian colonisation of Southern Spain can account for this peculiar outcome. Within a shorter time scope, the urbanization process of the Spanish population spiked in the 1960-1970´s (Collantes, 2019). Ever since then urbanisation rates grow, but at a slower pace (Gutiérrez, Moral-Benito & Ramos, 2020). The share of population inhabiting small towns appears to remain constant over the last five decades (Gómez Valenzuela & Holl, 2024).

In line with the European Union´s *Long term vision for rural areas* (European Commission, 2021), the Spanish strategic visions for rural areas point to remote work as an opportunity to smooth the depopulation of non-urban areas. The Spanish strategy against rural depopulation (Gobierno de España, 2019) stresses the importance of improving broadband connectivity, guaranteeing access to basic public services and infrastructures and favouring remote work agreements within the private sector. The idea is to make it easier for people to work and study remotely while living in rural areas. For the Spanish case, some qualitative studies suggest that the possibility of remote work agreements is a factor behind migrations to rural areas close to urban centres (e.g.: Donaire, Galí & Romero, 2025).

3.2. Econometric model

We implement equation (3) as a linear ordinary least squares model with interaction terms to differentiate the direct impact of remote work on commuting distances from the impacts of its interactions with the amenity and housing utility differences between job and residential locations. Due to data limitations, we cannot observe the idiosyncratic preferences of an individual for a location over an alternative one. We instead include the idiosyncratic preferences for the place of residence. Let i denote the place of residence and j the place of work. In a slightly summarised way, our econometric model reads:

$$\begin{aligned} d_{ij} &= \beta_0 \\ &+ \beta_1 WFH \times A_{ij}^{(1)} + \beta_2 WFH \times A_{ij}^{(2)} + \beta_3 WFH \times A_{ij}^{(3)} \\ &+ \beta_4 WFH \times price_{ij} + \beta_5 WFH \times size_{ij} + \beta_6 WFH \times locals_i \\ &+ \beta_9 WFH \times age + \beta_{10} WFH \times sex + \beta_{11} WFH \times edu + \beta_{12} WFH \times kids + \varepsilon_{ij} \end{aligned} \tag{4}$$

In equation (4), WFH is the state variable: the probability of an individual to work remotely. It replaces the first term in the right-hand side of (3): the higher the probability of working remotely, the fewer commutes. The terms $A_{ij}^{(1)} - A_{ij}^{(3)}$ stand for differences in accessibility for three services: schools, supermarkets and restaurants. Variables $price_{ij}$ and $size_{ij}$ inform about the differences in prices and dwelling size between job and residential locations. We also include controls for the idiosyncratic preferences of individuals. The first control, $locals_i$, is defined at the level of the residential location as the percentage of employees that live in the same municipality in which they were born. The remaining controls are defined at the individual level: age, biological sex, holding a higher education degree and having kids in the household. Finally, ε_{ij} is the error term.

To control potential multicollinearity problems caused by the interaction terms, we subtract the mean from each variable in equation (4). Therefore, the coefficients for all non-binary right-hand side terms can be interpreted as the effect of a variable´s unit change over the regressand when all other regressors are at their mean values.

3.3. Data description

Our main data source is a subset of the 2021 Spanish Census microdata file. In this subset a considerable share of observations have been eliminated to preserve the statistical secrecy. However, our microdata subset contains information for 4,702,756 individuals, representing the 26.52% of the employed individuals between 16 and 64 years of age with known occupation, industry, place of work and place of residence. Our subset is representative at the national level, jointly for the occupation and biological sex strata.

To compensate for the lost observations, we weight our subset according to the marginal distributions of the sex and occupation strata. Table 1 provides the marginal distributions of the individual-level categorical variables we use in our regression analysis, both for our weighted subset and for the corresponding census population. The distributions across sex and occupations in our subset match closely those from the census population both for commuters to different LAUs (C) and those commuting within the same LAU (NC). Admittedly, the distributions across industries, education levels and presence of kids in the household differ slightly from those of the census population. However, the greatest deviation is for the presence of kids in the household, bellow 5 percentage points.

		Population			Weighted subset		
		Total	C	NC	Total	C	NC
Occupation	1	3.91%	3.55%	4.18%	3.96%	3,58%	4,23%
	2	19.37%	18.09%	20.30%	19.19%	17,81%	20,20%
	3	10.73%	9.66%	11.51%	10.79%	9,75%	11,55%
	4	10.08%	10.44%	9.82%	10.10%	10,44%	9,84%
	5	22.57%	23.18%	22.12%	22.54%	23,14%	22,10%
	6	1.96%	3.12%	1.12%	1.97%	3,17%	1,09%
	7	10.76%	10.18%	11.18%	10.79%	10,24%	11,19%
	8	6.33%	5.80%	6.71%	6.39%	5,86%	6,79%
	9	14.27%	15.97%	13.04%	14.27%	16,00%	13,00%
Industry	A	4.52%	3.58%	5.82%	4.36%	3,42%	5,68%
	B	0.10%	0.13%	0.07%	0.02%	0,03%	0,01%
	C	10.57%	11.84%	8.81%	9.72%	11,00%	7,93%
	D	0.18%	0.20%	0.16%	0.06%	0,06%	0,06%
	E	0.69%	0.73%	0.63%	0.28%	0,26%	0,30%
	F	6.60%	6.92%	6.17%	5.93%	5,91%	5,97%
	G	16.90%	17.83%	15.62%	18.24%	19,98%	15,81%
	H	5.16%	5.65%	4.48%	5.94%	6,36%	5,36%
	I	7.70%	6.47%	9.40%	6.53%	4,77%	9,00%
	J	3.07%	3.35%	2.69%	5.86%	7,47%	3,59%
	K	1.90%	1.87%	1.95%	3.29%	3,87%	2,48%
	L	0.71%	0.65%	0.79%	0.24%	0,06%	0,49%
	M	5.64%	5.37%	6.01%	6.51%	6,31%	6,79%
	N	6.30%	6.65%	5.81%	8.13%	8,79%	7,20%
	O	7.24%	7.21%	7.29%	4.20%	3,20%	5,59%
	P	7.22%	7.77%	6.46%	6.41%	6,38%	6,44%
	Q	8.64%	8.36%	9.03%	9.75%	9,83%	9,63%
	R	1.95%	1.85%	2.07%	0.61%	0,20%	1,17%
	S	2.74%	2.31%	3.32%	1.11%	0,35%	2,17%
	T	2.16%	1.26%	3.40%	2.82%	1,74%	4,32%
	U	0.01%	0.01%	0.01%	0.00%	0,00%	0,00%
Sex	Male	53.25%	50.06%	55.57%	53.41%	50,22%	55,75%
	Female	46.75%	49.94%	44.43%	46.59%	49,78%	44,25%
Education	High	47.32%	48.92%	43.54%	46.39%	44,76%	47,59%
	Non high	54.76%	51.08%	56.46%	53.61%	55,24%	52,41%
Kids	>1	71.77%			76.73%		
	0	28.23%			23.27%		

Table 1. Occupations, industries, sex, education level and presence of kids' distributions. Census and weighted subset data. **Source:** own elaboration.

To compensate for the lost observations, we weight our subset according to the marginal distributions of the sex and occupation strata. Table 1 provides the marginal distributions of the individual-level categorical variables we use in our regression analysis, both for our weighted subset and for the corresponding census population. The distributions across sex and occupations in our subset match closely those from the census population both for commuters to different LAUs (C) and those commuting within the same LAU (NC). Admittedly, the distributions across industries, education levels and presence of kids in the household differ slightly from those of the census population. However, the greatest deviation is for the presence of kids in the household, bellow 5 percentage points.

3.3.1. Response variable

The response variable in our model (d_{ij}) is the distance between workplace and residence of employed population between 16 and 64 years of age. We retrieve individual-level data on work and residential locations from a subset of the 2021 Spanish Census microdata. The data is given at the local administrative unit (LAU) level. The commuting distance between location pairs is given by the Euclidean distance between geographical centroids. Following Keeble, Owens & Thompson (1982), we calculate the commuting distance within a given LAU as:

$$d_{i=j} = \frac{1}{3}\sqrt{area_{i=j} \times \pi} \tag{5}$$

As the 2021 Spanish Census has been constructed relying on register data, it is possible that some of our observations with abnormally long commutes might be reflecting the fact that some individuals do not change their registered address when they move to work in a different location.

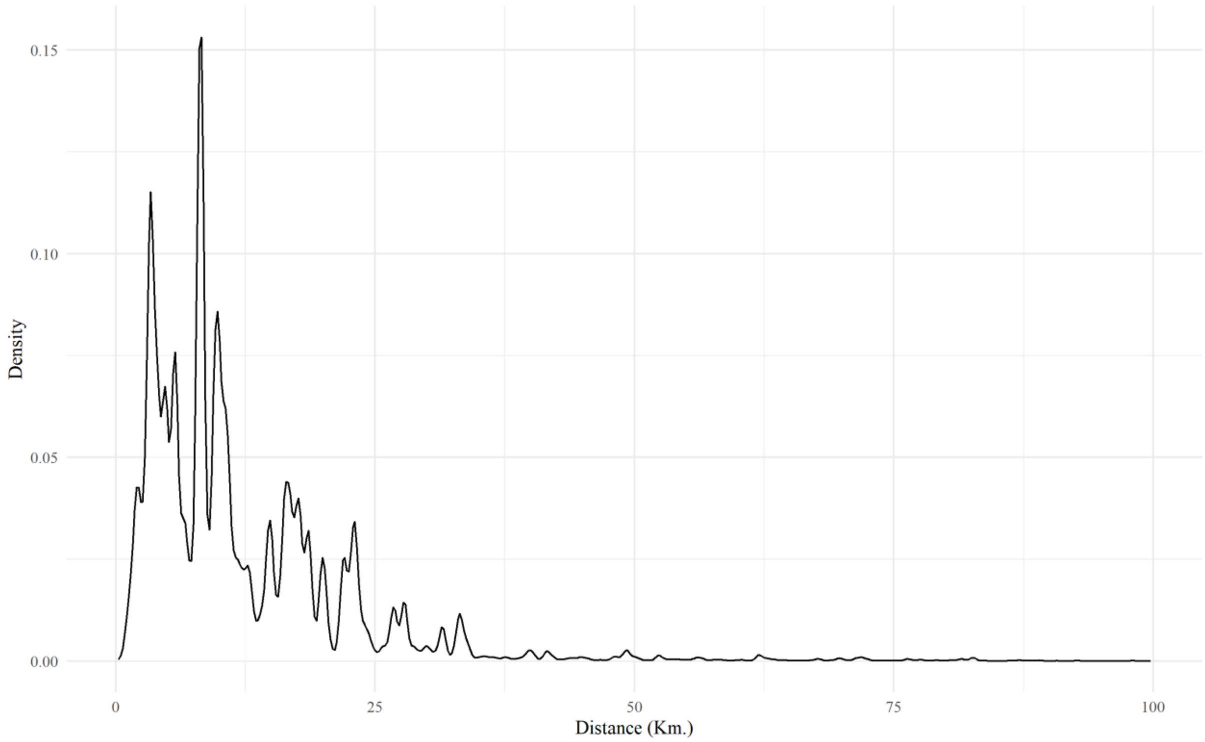

Figure 2. Distribution of commuting time. Gaussian kernel density function.
Source: own elaboration.

Figure 2 illustrates a left-skewed distribution of the dependent variable. As expected, most individuals live close to their workplaces. Most residential locations fall within the range of 25 kilometres away from workplaces. This suggests that, as of 2021 in Spain, the changes in migration patterns to/from towards rural areas (González-Leonardo, Rowe & Fresolone-Caparrós, 2022) had a limited effect on commuting distances.

3.3.2. State variable

The contribution by de Vos, Meijers & van Ham (2018) point to two problem-specific sources of bias when examining the relationship between remote work and commuting distances: reverse causality and preference-based sorting. Our design for the state variable—the probability of working from home—deals with the former. Reverse causality happens when longer commutes encourage individuals to work from home. It causes an overestimation of the effect of remote work on commuting distances. To deal with this source of bias, it is possible to introduce an instrumental variable in the model (e.g.: Zhu, 2012). We control for reverse causality in a different, yet related, way. We proxy remote work on the basis of occupation and industry technological characteristics. Our rationale it is more difficult for individuals to move across industries and occupations than to move from onsite to remote work within a given job. Coskun et al. (2024) use a similar approach to avoid endogeneity-related issues.

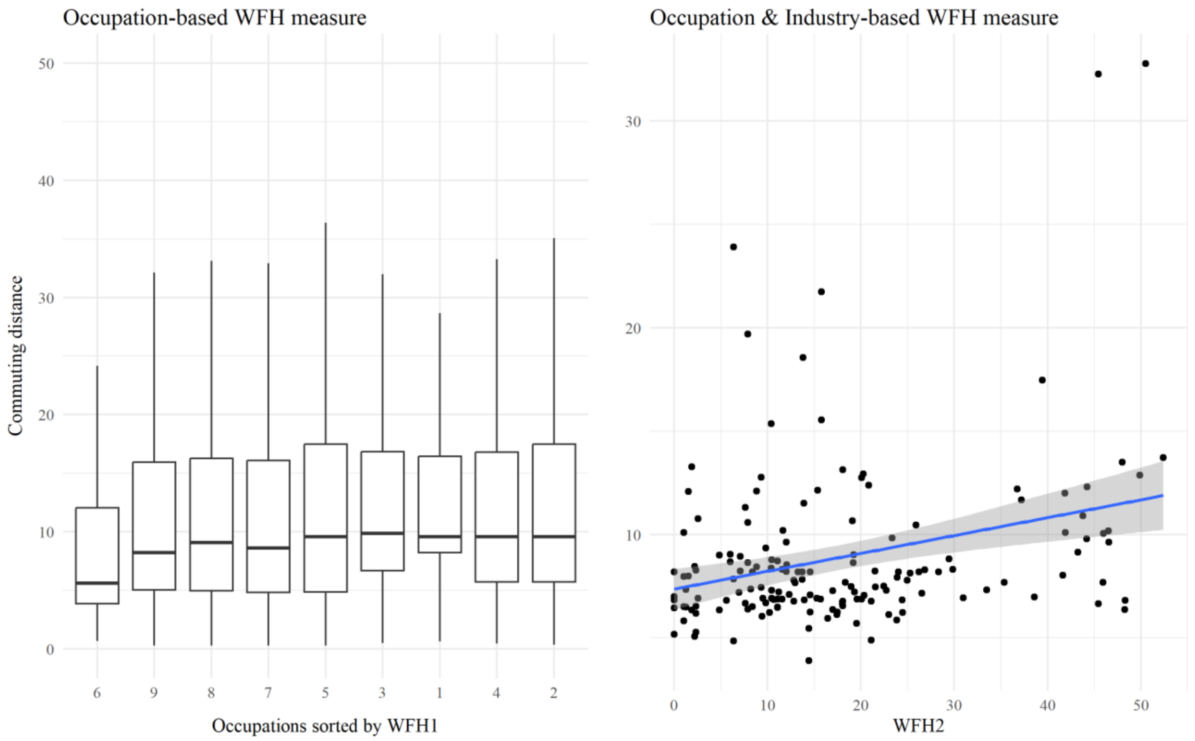

Figure 3. Correlation between remote work probability and commuting distances.
Source: own elaboration.

We propose two alternative measures of remote work probability instead. We define our first measure (hereafter, WFH1) on the basis of Eurostat´s (2021) skill-occupation matrices. These matrices break each occupation type into a set of skill coefficients that add to unity. For each occupation, we sum the coefficients corresponding to digital skills, as defined by Eurostat on the basis of Vuorikari, Kluzer & Punie (2022). Our second measure (WFH2) considers the probability of working remotely by industry as well. We calculate it multiplying WFH1 by the shares of jobs that can be done remotely by industry provided by Dingel & Neiman (2020) on the basis of US data. Consistent with our conceptual framework, both working from home proxy measures correlate positively with commuting distances (figure 3).

3.3.3. Control variables

Through our set of control variables, we aim to account for preference-based sorting. Preference-based sorting happens when, caeteris paribus, an individual chooses a farther (closer) location from the workplace due to her preferences. If these selection criteria remains unobserved, this could lead to a downward (upward) bias in the regression estimates for the impact of remote work on commuting distances. We elaborate on and extend the above-mentioned work of de Vos, Meijers & van Ham (2018) in three different directions. Tables 1 and 2 include a descriptive summary for all of our control variables.

	Units	Level	Max	Min	Median	Mean	S.D.
Distance	Km.	Individual	2195.33	0.27	9.56	14.86	39.81
State variables							
WHF1	%	Individual	63.13	25.41	46.51	46.91	13.23
WHF2	%	Individual	52.40	0.00	15.35	20.22	16.64
Amenities							
Schools	Dif. in Units / 1,000 inhab.	LAU	2.01	-4.02	0.00	0.00	0.11
Supermarkets	Dif. in Units / 1,000 inhab.	LAU	4.89	-6.11	0.00	0.03	0.33
Restaurants	Dif. in Units / 1,000 inhab.	LAU	16.44	-31.92	0.00	-0.12	0.99
Housing market							
Price	Dif. in index, 2015=100	LAU	19.60	-22.03	0.00	-0.30	2.11
Size	m^2	LAU	73.54	-58.95	0.00	0.60	12.95
Idiosyncratic preferences							
Locals	%	LAU	85.08	0.00	49.80	38.42	21.61
Age	Years	Individual	64.00	16.00	44.00	43.46	10.14

Table 2. Descriptive statistics for continuous variables in the econometric models.
Source: own elaboration.

First, we include amenity differentials between job and residential locations. Our intention is to bring the insights from the quality of life literature (Roback, 1982) into our empirical model. Schools and restaurants proxy the level of public services and non-tradable services respectively, at the closest local level as per Glaeser, Kolko & Saiz (2001), who stress the importance of public services for local attractiveness. We also include supermarkets as per Noguera et al. (2017) and Panori et al. (2024), claims supporting the importance of the access to convenience stores as a factor of local attraction. The amenity variables in (4) are defined as:

$$A_{ij} = A_i - A_j \tag{6}$$

where A_i and A_j are the level of a given amenity per 1,000 inhabitants measured for a given buffer around the residential (i) and job (j) locations. Following Kompil et al. (2019) we classify schools, restaurants and supermarkets as subregional services with a buffer consisting of a circle with a 10-kilometres radius around the location's centroid. As per the information sources, we retrieve school locations by LAU from the Spanish State Register of Non-university Education

Centres[1]. Our data on restaurants and supermarkets for each LAU comes from Open Street Map.[2]

Second, we include information on the housing market. The variables $price_{ij}$ and $size_{ij}$ are defined as in (6), albeit considering only the values corresponding to the residence and job LAUs—i.e.: without considering buffers around them. Regarding housing prices, we use the price local housing price index (base 2015) released by the Spanish National Statistical Institute (INE).[3] This statistic provides detail for the evolution of prices in 751 LAUs in Spain. For those LAUs not included, we take the price index of the corresponding NUTS3 region. Admittedly, these are not the housing price levels. Regarding the size of housing lots, The Spanish 2021 Census publicly available data provides average dwelling size for all LAUs.

Third, we include a control variable to proxy the presence of social networks that may influence individuals to take longer/shorter commutes ($locals_i$). We define this control as the percentage of employed individuals that were born in the LAU in which they currently live. Our rationale is that the higher this percentage is, the more likely it is for an individual to live in a given LAU because she has social and/or family networks there. Data at the LAU level is publicly available from the 2021 Spanish Census. This variable adds to more commonly used controls for location: age, biological sex, holding or not a higher education degree and the presence of kids in the household (as So, Orazem & Otto, 2001 among many others). We retrieve this latter set of variables at the individual level from our microdata subset from the 2021 Spanish Census.

4. Results

We run two versions of the econometric model described in equation (4), one for each remote work probability measure (WFH1 and WFH2). We include a dummy variable stating whether commutes take place within or across LAUs to control for zero-inflation in some of the regressors (see table 2). Furthermore, we compute standard errors clustered according to occupation, industry and whether commutes take place within or across LAUs. See Figures A1-A4 for the visual representation of residuals that informs this clustering choice. Finally, we estimate two naïve models without controls and compare the estimates for the WFH1 and WFH2 variables. This way, we test to what extent does preference-based sorting affect our results.

Table 3 summarises the regression results. In the four models, we find positive and statistically significant direct impacts of the WFH probability variables on commuting distance. Estimated coefficients for WFH in the models with control variables (2 and 4) are larger than in the two naïve models. We interpret this result as confirming the expected downward bias that can result from individuals' preference sorting. The overall fit of the model also improves when we include our control variables. But, admittedly, R^2 and adjusted R^2 values remain modest. All

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[1] Link to the dataset: https://www.educacionfpydeportes.gob.es/

[2] An editable map database built and maintained by volunteers and distributed under the Open Data Commons Open Database License. For further detail see: https://wiki.openstreetmap.org/wiki/Researcher_Information

[3] Índice de Precios de Vivienda. Available at: https://www.ine.es/

statistically significant coefficients for control variables show plausible signs except for the interaction term between WFH and price differences in model 4. Despite the variable transformation described in section 3.2, we do find some multicollinearity issues between regressors in models 4 (see tables A1 and A2 in the appendix). We conjecture that they are likely caused by the interaction terms in the regression.

				Dependent variable = Commuting distance
		WFH1 models		WFH2 models
	(1)	(2)	(3)	(4)
WFH	0.173^{*} (0.103)	0.358^{*} (0.188)	0.178^{*} (0.100)	0.470^{***} (0.204)
Schools		22.718^{*} (13.160)		20.496^{**} (12.611)
Supermarkets		2.427 (1.783)		2.125 (2.015)
Restaurants		-0.852 (0.660)		-1.072 (0.738)
Price		0.204 (0.224)		0.262 (0.264)
Size		0.265^{***} (0.045)		0.268^{***} (0.040)
Locals		38.490^{***} (9.309)		37.999^{***} (8.934)
Age		-0.208^{**} (0.082)		-0.188^{***} (0.064)
Sex = Woman		-1.128 (0.761)		-0.601 (0.565)
Education = High		0.294 (0.681)		0.180 (0.655)
Kids = Yes		-0.470 (0.574)		-0.416 (0.548)
C		-23.304^{***} (2.874)		-23.240^{***} (2.836)
WFH x Schools		1.933^{**} (0.897)		2.055^{*} (1.223)
WFH x Supermarkets		-0.091 (0.138)		-0.143 (0.138)
WFH x Restaurants		0.058 (0.077)		0.021 (0.051)
WFH x Price		-0.034 (0.024)		-0.033^{*} (0.018)
WFH x Size		0.006 (0.004)		0.007 (0.004)
WFH x Locals		1.761^{**} (0.742)		1.882^{**} (0.926)
WFH x Age		-0.015^{**} (0.007)		-0.015^{**} (0.007)
WFH x Sex = Woman		-0.068 (0.047)		-0.082^{**} (0.035)
WFH x Education = High		0.081^{*} (0.053)		0.063 (0.048)
WFH x Kids = Yes		0.179^{*} (0.097)		0.031 (0.058)
WFH x C		-0.585^{**} (0.247)		-0.644^{**} (0.306)
Intercept	14.826^{***} (1.299)	25.846^{***} (1.997)	14.605^{***} (1.233)	26.230^{***} (1.886)
Observations	670,290	670,290	670,290	670,290
R^2	0.003	0.090	0.006	0.103
Adjusted R^2	0.003	0.090	0.006	0.103
Residual Std. Error	202.509 (df = 670288)	193.479 (df = 670266)	202.279 (df = 670288)	192.128 (df = 670266)
F Statistic	$2,211.402^{***}$ (df = 1; 670288)	$2,889.847^{***}$ (df = 23; 670266)	$3,742.749^{***}$ (df = 1; 670288)	$3,342.126^{***}$ (df = 23; 670266)
Notes:	***Significant at the 1 percent level, **Significant at the 5 percent level, *Significant at the 10 percent level.			

Table 3. Regression summary results. **Source:** own elaboration.

Taking all variables on their average values, our regression models 2 and 4 predict a commuting distance between residence and job locations around 26 kilometres. Regarding the estimates for the state variable, taking all other variables on their average, an increase of 1 percentage point in the digital content of occupations (WFH1) would increase the commuting distance of individuals in 0.358 kilometres. The effect increases up to 0.470 kilometres when we consider our occupation- and industry-based measure for remote work probability (WFH2).

Within our limited set of amenities, our results suggest that accessibility to schools has a greater impact on commuting distances than accessibility to restaurants or supermarkets. Not only the coefficient size for schools is larger, but the relationship with the dependent variable is also more statistically significant. Interaction terms are positive and statistically significant as well. Out of the three amenities included as controls, education is the services that can substitute onsite interactions the less. Access to restaurants and supermarkets, on the other hand, can be partially substitute by home deliveries of prepared meals and groceries. We find this result interesting since, at least in Spain, regional governments can choose the distribution of schools across space discretionally to some extent (Colino, 2020). Therefore, preserving existing or promoting new schools in rural or intermediate areas might be a way to attract remote workers and decongest urban agglomerations. This result is also consistent with the findings by San-Martín González & Soler-Vaya (2024), pointing to the role that access to public services plays in containing rural depopulation.

Regarding the housing market variables, we do not find significant evidence supporting that higher price differences between the place of work and the place of residence correlate with higher commuting distances. This result is likely related with our variable measurement, since we can only observe price variations and not price levels. We do observe is a positive and statistically significant impact of dwelling sizes on commuting distances. An increase in the difference between the job and residential locations' dwelling sizes of 1 m^2 is associated with an increase in commuting distances of 0.265 kilometres—again, with all other variables at their mean. We do not find, however, statistically significant interactions between the dwelling size variable and WFH1 or WFH2 which we would expect given the demand of remote workers for space to work from home.

Finally, some proxies for idiosyncratic preferences seem to impact commuting distances as well. First and foremost, the percentage of employed individuals living at the same LAU in which they were born is a strong predictor of commuting distances. It correlates with higher commutes, suggesting that individuals are willing to take longer distances to their workplaces to stay close to their social and family networks. As per individual characteristics, we find a negative relationship between age and commuting distances. Shall this result be confirmed, this would imply that remote work could be a channel to countermand outmigration of younger cohorts from non-urban areas (García Marín & Espejo Marín, 2019). Being a woman correlates negatively with commuting distances, which is consistent with much of the empirical literature (see Lee et al., 2022 for a recent review and some nuanced results in the US). However, the coefficient is only statistically significant for the interaction term with WFH2 in model 4.

Finally, the coefficient for interaction terms between WFH1 and the education and kids' variables is positive and statistically significant as well.

5. Concluding remarks

In this paper we explore whether there are certain amenities that, combined with the possibility of working from home, allow for longer distances between job and residential locations in Spain. We find that differences between accessibility to schools in the job and residential locations relate with longer distances between job and residential locations according to the 2021 Census data. We also find positive interactions of this variable with the probability of working from home. Shall public services be a factor that can influence remote workers to live further away from their workplaces, their provision in intermediate and rural areas could be seen as viable strategy to tackle the demographic decline in some parts of the Spanish territory.

A number of limitations and future research avenues arise from the present work. First, we would like to account better for the differences in amenity accessibility for commuters within the same LAUs. Reducing this control to a dummy variable might be a source of bias in our results. Second, since our data matches the marginal distributions of the census for a number of variables both for commuters in the same LAU and across LAUs, it would be possible to run separate regression models for these two subsets of individuals. Third, we look forward to expanding our set of amenities. Perhaps it could also be interesting to group them according to a given classification (e.g.: as in Kompil et al., 2019) or using principal component analysis (in a similar way as Robbennolt et al., 2024). Finally, using our results to produce scenarios to be tested for impacts in a macroeconomic model (as Spithoven & Merlevede, 2025) is yet another possible extension.

6. References

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7. Appendix

7.1. Checks for potential multicollinearity

	1	2	3	4	5	6	7	8	9	10
(1) Distance	1.000									
(2) WFH1	0.057	1.000								
(3) WFH2	0.075	0.685	1.000							
(4) Schools	0.045	0.051	0.059	1.000						
(5) Supermarkets	0.026	0.034	0.051	0.281	1.000					
(6) Restaurants	-0.025	0.033	0.032	0.108	0.159	1.000				
(7) Price	0.010	0.044	0.029	0.006	-0.017	0.150	1.000			
(8) Size	0.059	0.096	0.071	0.339	0.375	-0.030	0.033	1.000		
(9) Locals	0.004	-0.039	-0.081	-0.156	-0.348	0.072	0.116	-0.348	1.000	
(10) Age	-0.063	-0.063	-0.036	0.019	0.019	-0.008	0.031	0.056	0.002	1.000

Table A1. Correlation matrix for continuous variables. All correlations statistically significant at the 1 percent level.
Source: own elaboration.

	(2)	(4)
WFH	9.355	11.836
Schools	1.251	1.208
Supermarkets	1.499	1.450
Restaurants	1.251	1.327
Price	1.157	1.099
Size	1.614	1.691
Locals	1.705	1.697
Age	1.030	1.021
Sex	1.049	1.049
Kids	1.045	1.042
Education	2.041	1.584
C/NC	1.437	1.428
WFH x Schools	1.191	1.306
WFH x Supermarkets	1.462	1.689
WFH x Restaurants	1.304	1.354
WFH x Price	1.160	1.111
WFH x Size	1.546	2.043
WFH x Locals	1.701	2.041
WFH x Age	1.047	1.032
WFH x Sex = Woman	1.972	1.980
WFH x Education = High	4.546	4.590
WFH x Kids = Yes	2.780	4.673
WFH x C	2.466	2.596

Table A2. Variance of inflation factors for the regressors in models 2 and 4
Source: own elaboration.

7.2. Residual plots for the regression models with control variables

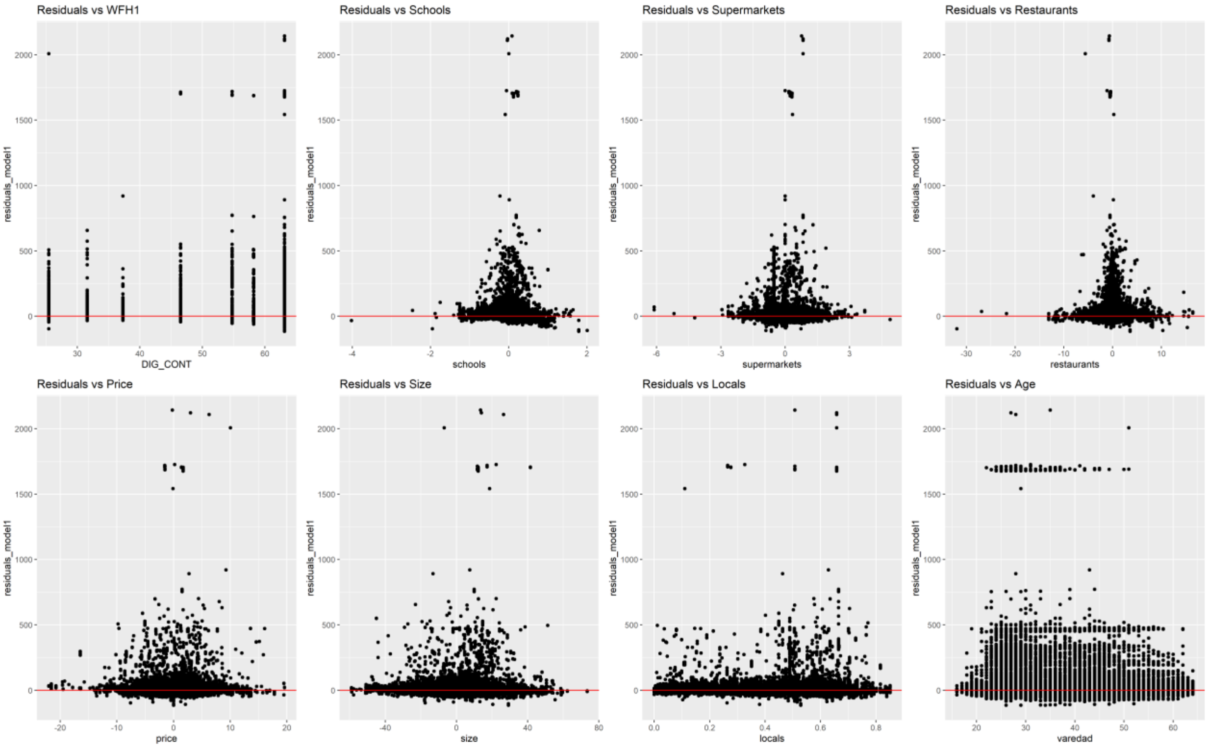

Figure A1. Residual plots for continuous regressors, model 2.
Source: own elaboration.

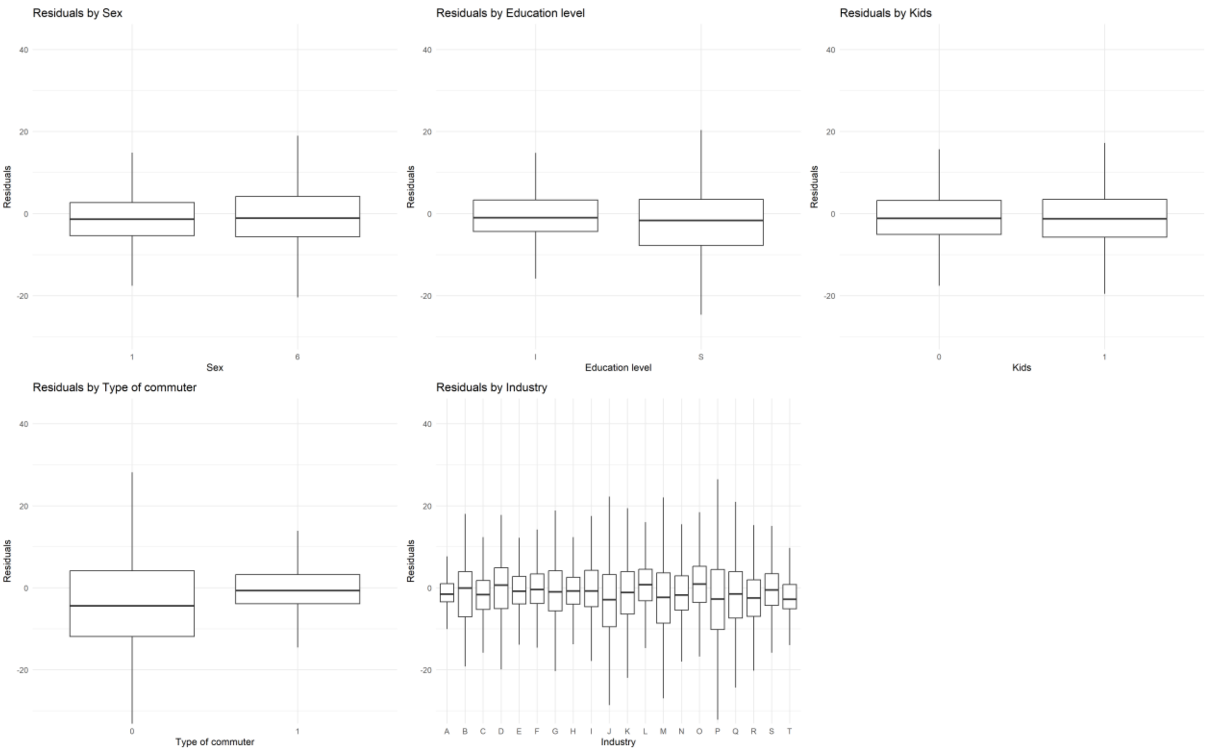

Figure A2. Residual plots for categorical regressors, model 2.
Source: own elaboration.

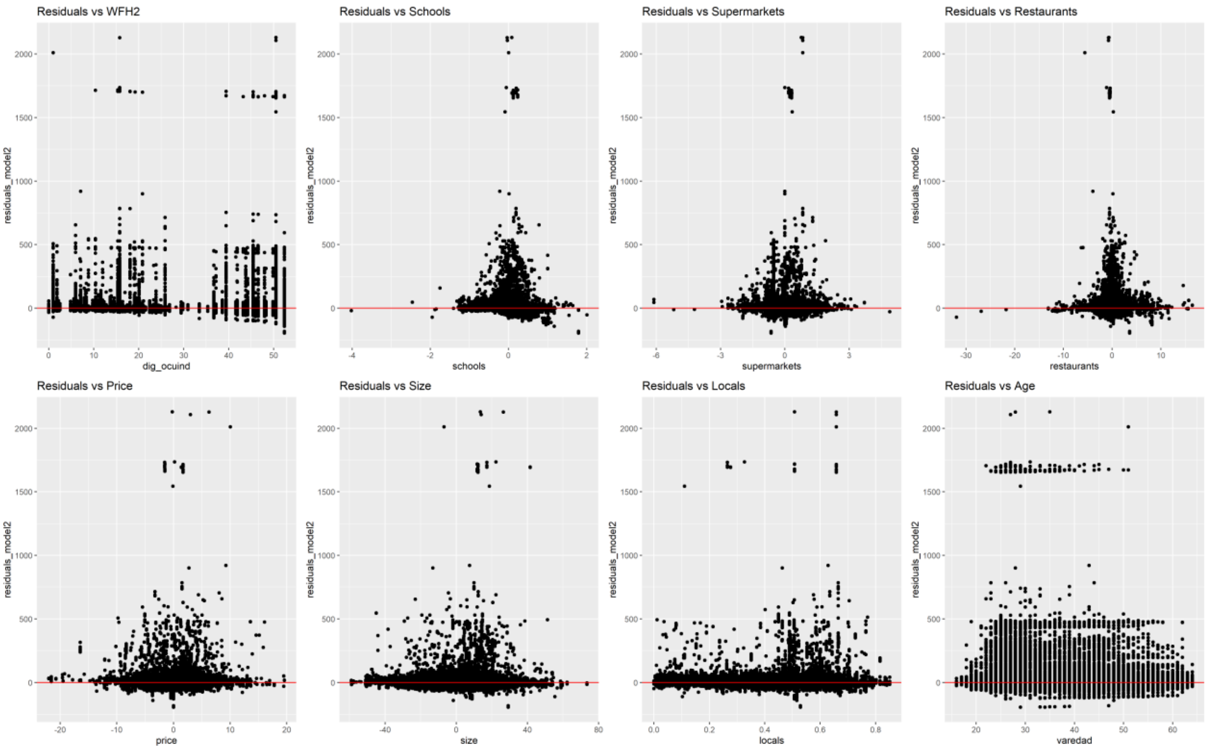

Figure A3. Residual plots for continuous regressors, model 2.
Source: own elaboration.

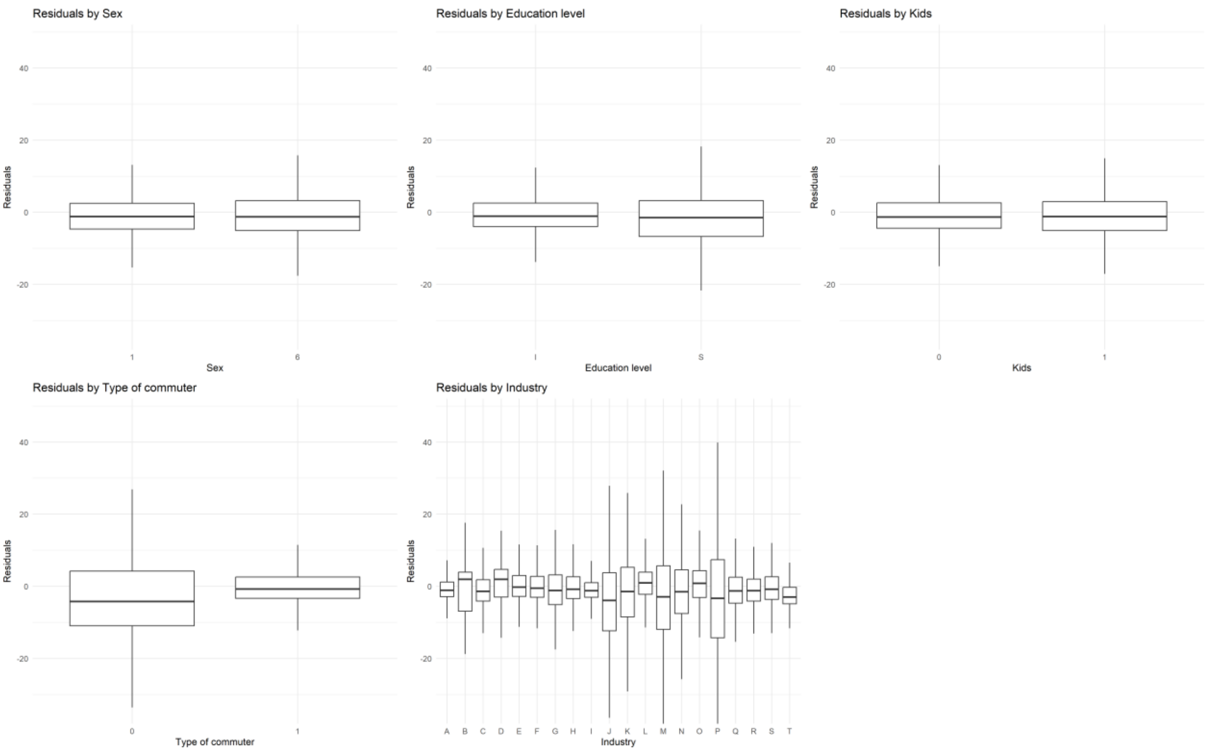

Figure A4. Residual plots for categorical regressors, model 2.
Source: own elaboration.