Centre of Excellence for Science and Innovation Studies

CESIS Electronic Working Paper Series

Paper No. 498

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February 2025

The Royal Institute of technology
Centre of Excellence for Science and Innovation Studies (CESIS)
http://www.cesis.se

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Abstract

In this paper, we investigate how the lockdown-induced exposure to remote work affected the likelihood of switching to longer commutes using a longitudinal full-population register of Swedish employees. We find that employees with little experience of longer commutes were more likely to start commuting longer if they had occupations with high potential for remote work. Examining heterogeneity across sectors, this is especially evident among high-skilled workers in sectors with low pre-existing shares of remote work and longer commutes. Our findings are important for understanding regional expansion and spatial extensions of labour markets in a world where more work can be done remotely.

Keywords: Labour mobility; Commuting distance; Remote work: Knowledge-intensive sectors; Covid-19
JEL Codes: R1; R3; J6; J2

[1] This research is funded by the Swedish Research Council Formas, grant 2021-02223. We thank participants at the Western Regional Science Association (WRSA) 63rd Annual Meeting in Monterey (CA), 2024, for comments and suggestions on an earlier version of the paper.

1. Introduction

The Covid–19 pandemic and ensuing lockdowns sent shocks through the geographical and social organization of work and caused drastic changes in peoples work lives, forcing many to work from home for the first time across a broad spectrum of occupations. A critical question that has emerged in the wake of the pandemic is how the Covid-19 induced Working from Home (WFH) shock has affected workers' location choices and commuting behaviour (Delventhal et al., 2022; Althoff et al., 2022; Caselli et al., 2022; Kyriakopoulou and Picard, 2023; Brueckner et al., 2023; Bick et al., 2023; Davis et al., 2024). Has the pandemic resulted in lasting effects on labour mobility and have longer commutes become more common? In this paper, we examine how workers' commuting behaviour changed in response to the pandemic with a particular focus on their likelihood to switch to longer commutes and how that probability is affected by occupational characteristics.

The possibility of promoting efficiency of labour markets and of personal freedom in tandem has sparked interest of policy makers and researchers in the question of who can and will subject themselves to longer commutes (Corazza and Musso, 2021; Martinus et al., 2020). More people commuting longer to reach their workplace reflects labour market enlargement and increasing job accessibility as externalities associated with large labour markets, such as better matching and higher productivity, can spread over larger areas (Monte et al., 2018). A highly relevant but so far unexplored question is how the drastic shift to remote work during the pandemic has affected commuting over long distances. Such knowledge is key for understanding the effects of distance work on the size and functioning of local labour markets.

The first contribution of this paper is to provide a quantitative assessment and decomposition of change in commuting distance before and during the pandemic (2015-2021). We use detailed registry data on employees (N=900,873) that contain geocoded information on their workplace and residential location, industry and occupational belonging and socioeconomic characteristics. In this initial descriptive analysis, we find a large increase in the extent of longer commutes, which is especially evident among workers in knowledge–intensive sectors with occupations that score high on WFH potential, but also in sectors with pre-existing low shares, such as in knowledge-intensive public sectors. The second contribution is that we provide estimation based evidence on the probability of employees switching to longer commutes and how that probability is affected by WFH potential of the occupation and exposure to remote work. To this point, we still lack evidence based on individual-level data to help us understand changes in commuting in response to the pandemic. Nevertheless, a common argument is that in order to fully understand the mobility effects of the pandemic, it is crucial to account for complexity at the level of individuals (Adams-Prassl et al., 2020; Adams-Prassl et al., 2022). Existing studies based on microdata have profoundly examined if workers in occupations with high potential for remote work are more inclined to make counterurban moves in response to the pandemic (Tønnessen, 2021; Correa, 2023; Vogiazides and Kawalerowicz, 2023: Eliasson, 2023). These studies show a positive relationship between remote work potential and urban (or inner city) out-migration, but the magnitude is often small in relation to other mobility drivers. A disadvantage is the lack of a unified urban-rural typology and definition of what constitutes a counterurban move, making results difficult to parallel.

In this study, we investigate how varying WFH potential and exposure to remote work affected the likelihood to switch to longer commutes, regardless of destination. We find robust evidence that workers with very little (or zero) previous experience of longer commutes were more likely to start commuting longer during the pandemic if they had occupations with high WFH potential. We provide further evidence of heterogeneity across sectors by contrasting high-skilled workers in private vs. public sector jobs. The rationale is to examine if varying exposure to remote work during the pandemic influenced the probability to switch to longer commutes. Our findings suggest that the pandemic has altered labour mobility in favor of longer commutes relatively more among high-skilled workers in the public sector where commuting and remote work was less widespread, before the pandemic. The nature of many jobs in central (non-local) government institutions have traditionally mandated a high degree of onsite attendance, but this came to change during the pandemic (Kim and Horner, 2021). According to the Swedish National Audit Office (NAO, 2023), the spread of Covid-19 in Sweden implied a rapid transition to working from home across sectors, which was particularly extensive in the non-local government sector, where 40–60% of employees periodically worked from home for at least half of the working day. This was significantly more than in other sectors. If WFH is here to stay (Bartik et al., 2020; Barrero et al., 2021), it is important to understand how it will influence commuting in occupations with relatively low pre-existing shares. The existing literature has not dug deeper into this heterogeneity, which is despite the argument that exposure to remote work should entail longer commutes (Putri and Amran, 2021; Aliopour et al., 2021; Delventhal et al., 2022).

Although it is difficult to account for all the mechanisms at work when individuals sort themselves into occupations with varying potential for remote work, we take several measures to reduce selection. Exploiting the panel nature of the data, the analysis accounts for unobserved heterogeneity at the level of individuals, industries and occupations. The model is further specified to account for additional selection mechanisms that influence the potential for employees switching to longer commutes, such as extent of employment (full vs. part-time work), job position, education, incomes, dual homeownership and family situation. Previous studies often disregard complexities at the individual and family level and evidence from pandemic years is mainly based on cross-sectional data, which fails to account for change over time. In addition, the analysis follows individuals over several years both before and during the pandemic to account for time-varying socioeconomic and job-related factors. Our findings adds to a growing literature on how commuting at the individual level was affected during lockdown (Tønnessen, 2021; Correa, 2023; Vogiazides and Kawalerowicz, 2023; Eliasson, 2023). In all, we are confident in our assertion that people who were more exposed to distance work during the pandemic lockdowns were more likely to switch to long-distance commuting. To what extent these changes can can be considered permanent depends on the reasons underlying the change, which can be partially assessed based on and the characteristics of those that switched, which we also discuss in this paper.

The rest of this paper is structured in the following: Section 2 reviews the relevant literature and the theoretical arguments underlying the study. Section 3 outlines the data and the methods and presents summary statistics regarding the change in commuting distances before and during the pandemic, across industries. Section 4 presents the main results emerging from the analyses and Section 5 concludes the paper.

2. Background and literature

The literature on commuting shows that economies are becoming gradually less dependent on fixed locations of workplaces and workers are seen to commute increasingly longer to reach their workplace (Goetz et al., 2013; Haas and Osland, 2014). Andersson et al. (2018) show that the Swedish long-distance commuting population grew by 42% during 1990-2009, of which the largest fraction constituted rural to urban commuters. They further show that the most common pathway into such commuting, pre-pandemic, was via change of workplace—employees living in rural regions becoming employed in urban regions. Engaging in long-distance commuting represents a significant decision, implying that it must offer benefits commensurate with the costs to justify the effort. Prior studies have identified common drivers ranging from the socioeconomic and occupational profiles of individuals to spatial-temporal transformations in the labour market. Influential factors relate to income, demographics and family situation and individuals that engage in longer commutes are often male, relatively young and childless (van Ham and Hooimeijer, 2009). They are also associated with higher earnings (Dargay and Clark, 2012) and occupations with greater flexibility for remote work (Clark et al., 2003). The effects of socioeconomic characteristics are however not straightforward and depends on the underlying reasons as long-distance commuting can function both as an alternative to migration and as a trigger of migration (Eliasson et al., 2003; Clark et al., 2003; Sandow and Lundholm, 2020; Tsiopa et al., 2024).

Studies show that employment in certain types of public sector jobs which are evenly distributed across the country (teachers in primary and secondary schools, doctors, nurses), decreases the likelihood of longer commutes (Sandow, 2008). This is also true for many local and non-local public/government jobs, with varying skill-requirement, as the nature of such work has traditionally mandated high onsite attendance (Öhman and Lindgren, 2003). Employment in other sectors, such as ICT and finance, often provides more flexibility for remote work, and reduces the necessity for daily long-distance commutes (van Ommeren et al., 2005). Therefore, employees in these sectors may find it feasible to commute long distances less frequently, given the option to work from home part of the week. Research conducted during pre-pandemic year's shows that occupations in the private sector and those characterized by tasks that can be done digitally, often skill-intensive jobs, inherently lend themselves to greater flexibility, including the option to work from home (Rüger et al., 2021; de Vos and van Ham, 2018; Brouwer et al., 2022). While the existing literature provides a comprehensive understanding of the socioeconomic characteristics of long-distance commuters, their industry and occupational belonging, there are gaps in terms of understanding the changes that have occurred in response to the pandemic.

2.1 Changing commuting patterns in response to the pandemic

Studies that document change in commuting and remote work during the pandemic show a persistent rise in remote work and reductions in daily commutes, especially in industries with high skill-level (Bick et al., 2023; Barrero et al., 2023). A recent report from the union of Sweden's engineers shows an increase of their members' commuting distances with over 20% (almost 10 km) during 2020-2024 (Kreicbergs and Ohlin, 2024). High-skill occupations often have work arrangements and mobility options that are different compared to other occupations, with higher flexibility, high rate of analytical and computer-intense tasks and workplaces that tends to cluster in larger cities. These occupations also share certain characteristics that can facilitate and incentivize remote work, such as higher wages that can compensate for the cost of commuting (Alipour et al., 2021). A key assumption in the literature is that the adoption of new work arrangements (during the pandemic) induced workers to adjust their location choices and commuting behaviours (Vogiazides and Kawalerowicz, 2023). This mechanism is formally outlined in Delventhal, Kwon and Parkhomenko (2022) who predicts that massive teleworking will cause workers to move to the periphery, driven most profoundly by commuting preferences and search for more affordable housing. Workers who previously commuted can work more extensively at home, and while average commuting times fall— commuting distance increases. The shift to remote work and longer commutes is expected to provide benefits to those who can work more from home and suffer less disutility from commuting, but also to those who still have to commute as congestion reduces and commuting speeds increases (Kyriakopoulou and Picard, 2023).

Previous research clearly shows how socioeconomic conditions, occupational characteristics and regional factors (e.g., house prices) play pivotal roles in explaining workers commuting behaviours. We note, however, that the existing evidence during the pandemic is mostly based on data from the

US and UK and there is still uncertainty regarding the outcomes in countries with very different labour conditions and housing markets.

3. Data

In order to track changes in commuting distances at the individual level, we combine data from several population registries, e.g. the Longitudinal Integration Database for Health Insurance and Labour Market Studies (LISA) and the Geographic Database (GDB). The data originate from Statistics Sweden and we use information on individuals' occupational status to distinguish employees in the age group 25–64. The rationale for excluding the youngest (aged 16-24) is that they are generally less established on the labour market and they often have incorrect residential information, i.e., registration at their parents' address (Amcoff, 2009). We also exclude individuals older than 64 years, due to the traditional retirement age, which is around 65 years in Sweden. We further restrict the sample by excluding those with missing information in any given year on residence and workplace coordinates and as well as those with multiple workplaces to facilitate calculation of residence–workplace distances. The resulting dataset is a panel of 900,873 employees observed across industries and occupations over the period 2015-2021.

3.1 Measuring long-distance commutes

There is a large literature focusing explicitly on workers that subject themselves to longer commutes (Green et al., 1999; Öhman and Lindgren, 2003; Champion et al., 2009; Dargay and Clark, 2012; Eliasson et al. 2003; van Ham et al., 2001; Limtanakool et al., 2006; Wrede, 2013; Brown et al., 2015; Sandow, 2008; Andersson et al., 2018). In this literature, a distance of 50 kilometres between home and work is often considered as a minimum to distinguish the long-distance commuters. This builds on the assumption that 50 kilometres approximates the maximum limit of time an individual is willing to spend on commuting one way to work, i.e. about 45 minutes up to an hour (Johansson et al., 2002; Sandow and Westin, 2020). We build on this literature and define the outcome variable in the following:

$$y_{it} = \begin{cases} 1, \ if \ d_{it} \geq \sigma \ and \ d_{it-n} \ngeq \sigma \ \forall \ T \\ 0, \ if \ d_{it} \ngeq \sigma \ \forall \ T \end{cases} \tag{1}$$

where d_{it} denote the geographical distance between the residence and the workplace of employee i at time t, σ denote the distance threshold (50+ km) and T denote the time dimension. In calculating d_{it}, we use geocoded information on the location of the residence and the workplace to obtain the geographical distance with 250*250 meters or 1000*1000 meters precision, depending on whether the focal employee is registered as living in an urban or rural area. Our definition implies that employees for which $y_{it} = 1 \ \forall$ T and those with any experience of long-distance commuting since year 2000 are excluded ($\mathrm{T} = 2000, \dots, 2021$). This implies that we make use of the time dimension in the data and focus on the change in commuting status at the individual level. This also implies that we restrict the analysis to those who are new long-distance commuters, which has the advantage to reduce the potential bias arising from any previous experience, i.e., the so called *habitual* effect of long-distance commuting (Sandow and Westin, 2010; Prillwitz et al., 2007). In the analysis, we also account for the nature of the change in commuting by combining information on residential–workplace distance, workplace identity and residential relocation to indicate if a change in the outcome, y_{it}, is the result of a residential move or a change in workplace. Similar to previous studies (e.g., Andersson et al., 2018; Sandow and Westin, 2010), we do not have access to travel time in the data and we therefore use geographical distance to proxy commuting distance. With the available data, it is also not possible to distinguish long-distance daily from weekly commuters, therefore both groups of commuters are included in our analysis while controlling for dual homeownership.

3.2 Changing trends in commuting before and during the pandemic

Figure 1 shows how the number of new long-distance commuters has evolved over the time period in focus, computed according to Eq. (1). The figure shows a decline during pre-pandemic years followed by a rapid rise after the start of the pandemic, most notably between November 2019 and November 2020. Similar patterns of increasing commutes during the pandemic emerge when we graph the share of employees across industries that commute longer distances to work, both 50+ km and 100+ km (see Figure S1 in the supplemental material). The share of employees who commuted longer than 50 km increased with on average 16% between 2015 and 2021, and the largest increase occurred between 2019 and 2021 (+14%). Using larger cut-of points for the distance threshold, the starting points are different, but the time trend evolve quite similarly over time.

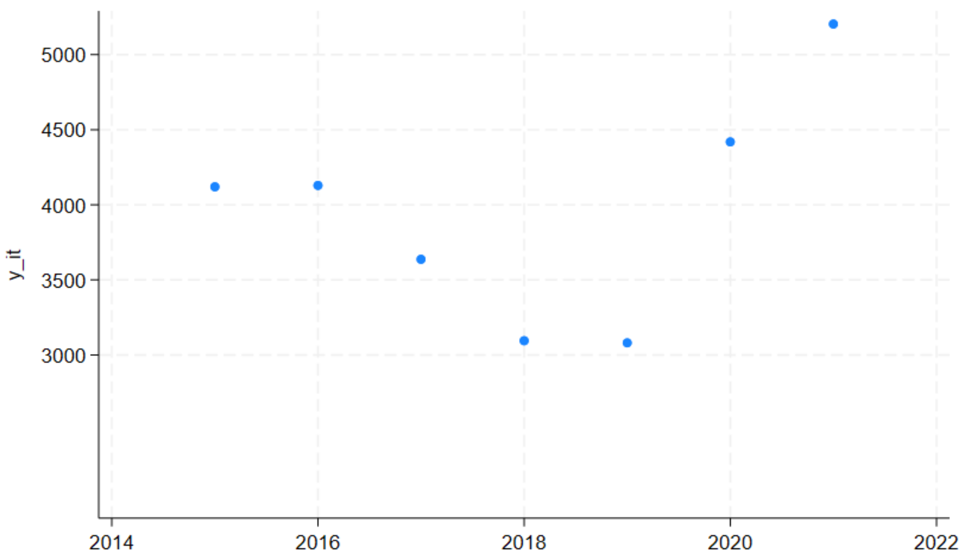

Fig 1. Extent of long-distance commuting during 2016-2021 with y_{it} defined by Eq. (1) on the y-axis.

A group of workers of particular interest in studies of commuting are the high-skilled, who often have jobs in knowledge-intensive sectors with work arrangements and mobility choices that are very different from other sectors. This involves higher flexibility, more irregular commutes and higher potential to perform the work from home (Champion et al., 2009; de Vos et al. 2018; Adams-Prassl et al., 2022). Figure 2 and 3 display how long-distance commuting changed after the start of the pandemic across knowledge-intensive sectors and occupations calculated using industry and occupational codes and the industry definitions outlined in Table 1. Increases are especially evident in the private business sector and the financial sector (Figure 2) and in occupations associated with a higher educational requirement (Figure 3), but are also evident in local and non-local governmental authorities and higher education institutions.

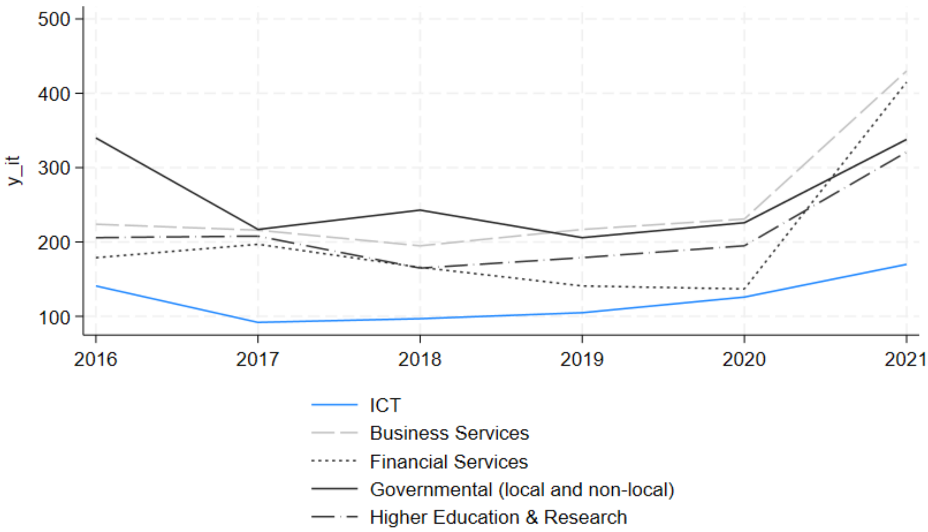

Fig 2. Extent of long-distance commuting (y_{it}) during 2015-2021 in knowledge-intensive sectors based on workers industry belonging by 2-digit Standard Industrial Classification Codes (SNI).

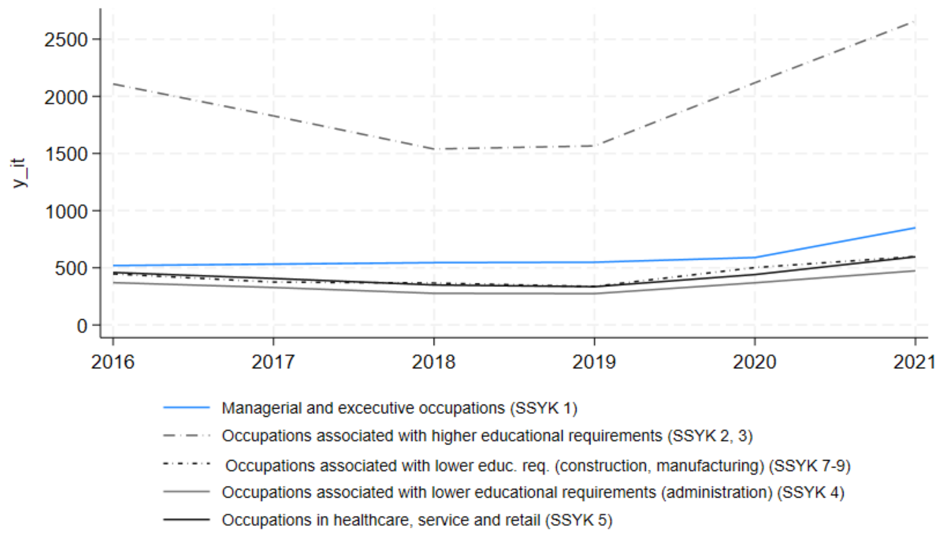

Fig 3. Extent of long-distance commuting (y_{it}) during 2015-2021 across occupations with varying skill-level based on workers occupational belonging (1-digit SSYK/ISCO).

Examining pre and post pandemic mean and median residential-workplace distances (Fig. S2 and S3) and the extent of workers who started to commute longer distances (Fig. 2 and 3), we observe several noteworthy patterns. The first thing that stands out is the great heterogeneity that exists across sectors with skill-intensive jobs. The average residential–workplace distance in the private knowledge-intensive sectors is rising over time and is well above the average over the period, especially among workers in the private business sector and the financial sector. The second is the rapid increase in new long-distance commuters in sectors traditionally associated with lower flexibility in terms of remote work arrangements, such as the public/government sector. Public sector jobs are more evenly spread in geography and studies on labour mobility have not found long distance commuting and remote work to be a widespread phenomenon in these sectors, before the pandemic (Dingel and Neiman, 2020; Andersson et al., 2018). Regarding change over time, it seems like the pandemic has accelerated a pre-existing trend of rising long distance commutes most notably among workers in ICT jobs (computer programmers, IT consultants).

Table 1. Decomposition and definition of knowledge-intensive sectors.

Sector	Definition by 2-digit Swedish standard industrial classification code SNI)
Information & Communication	Computer programming, consultancy and related activities, ICT (62).
	Media, broadcasting, publishing and related activities, IC (63).
Business Services	Legal, accounting, management consultancy, architectural, engineering, advertising and market research and related activities (69, 70, 73).
Financial Services	Insurance and pension funding and activities auxiliary to financial services and insurance (64-66).
Public Administration	Governmental administration of non-local (state/central government administrative authorities) and local government (84).
Research & Development	Tertiary research and education (85).

Note: Our definitions broadly follow the Eurostat classification of knowledge-intensive private and public sectors with the modification that Public Administration excludes employees in armed forces (military, defense services) and veterinary services. Research & Development does not include primary and secondary education.

3.3 Individual and family characteristics

Table 2 shows summary statistics for the variables included in the model, comprising a measure of WFH potential. Most of the variables are self-explanatory (detailed variable definitions are displayed in Table S1) and the variable in focus is the measure of WFH potential. We use the occupational codes present in the data and the occupational index developed in Sostero et al. (2023) to define this variable. This index builds on previous occupational classifications (Dingel and Neiman, 2020) in grouping occupations based on their task content, with modifications to fit a European context. We use 3-digit SSYK codes to construct the continuous measure that varies from 0 to 1, where 1 denotes occupations with the highest potential to be performed remotely.

Table 2 shows that the WFH index is higher among those that switched to long-distance commuting after the start of the pandemic (0.5-0.52) compared to the average across all employees (0.35). The index is also indicated to increase as the pandemic progressed. Figure S4 illustrates how the WFH index correlates with the length of commutes observed in the data showing that it captures differences between occupations; longer commuting distances are associated with more remote compatible jobs. Summary statistics further show that those that switched to long-distance commuting during the pandemic did more often have dual homes, were on average older and had slightly higher incomes compared to those that switched in pre-pandemic years. The extent of employment ('Full-time employee') was lower among those that started to commute long distances after the start of the pandemic, compared to before. A switch to long distance commuting during the pandemic did also more often follow a change in residential location compared to a change in workplace.

Table 2. Variables and summary statistics; mean (standard deviation) before and during the pandemic

Variable	Non-switchers	Switchers (new long-distance commuters +50 km) (y_{it})		
	2015-2021	2019	2020	2021
WFH potential	0.346	0.509	0.477	0.514
	(0.445)	(0.463)	(0.462)	(0.459)
Age	47.16	45.62	47.54	49.45
	(9.49)	(10.01)	(10.17)	(10.58)
Gender (male=1)	0.469	0.546	0.598	0.523
	(0.499)	(0.497)	(0.490)	(0.499)
Income	368.432	453.765	470.441	590.212
	(250.828)	(308.259)	(385.221)	(601.704)
Full-time employee	0.957	0.808	0.820	0.676
	(0.204)	(0.393)	(0.383)	(0.467)
University	0.072	0.110	0.091	0.106
	(0.259)	(0.313)	(0.288)	(0.308)
PhD	0.008	0.010	0.012	0.017
	(0.091)	(0.094)	(0.103)	(0.130)
Single no children	0.160	0.170	0.180	0.172
	(0.366)	(0.376)	(0.384)	(0.378)
Married/cohabitated	0.221	0.273	0.276	0.309
no children	(0.415)	(0.445)	(0.447)	(0.462)
Married/cohabitated children	0.454	0.374	0.377	0.341
(<5 years)	(0.497)	(0.484)	(0.484)	(0.474)
Family income	6195.102	6975.409	7027.995	8718.034
	(21795)	(8339.368)	(7804.321)	(10853.27)
Residential relocation	0.054	0.331	0.298	0.483
	(0.226)	(0.470)	(0.457)	(0.499)
Urban/Metro residence	0.686	0.616	0.553	0.557
	(0.463)	(0.486)	(0.497)	(0.496)
Urban/Metro workplace	0.712	0.770	0.795	0.812
	(0.452)	(0.420)	(0.403)	(0.390)
Dual homeowner	0.052	0.067	0.075	0.083
	(0.222)	(0.249)	(0.263)	(0.275)
House price (municipality)	3681	3383.556	3399.914	3970.831
	(2125)	(1766.45)	(1858.46)	(2135.256)
ICT	0.021	0.034	0.028	0.032
	(0.144)	(0.181)	(0.166)	(0.177)
IC	0.001	0.003	0.002	0.002
	(0.034)	(0.056)	(0.045)	(0.045)
Business Services	0.035	0.070	0.052	0.082
	(0.184)	(0.255)	(0.222)	(0.275)
Financial Services	0.025	0.045	0.031	0.079
	(0.125)	(0.209)	(0.173)	(0.271)
Public administration	0.057	0.066	0.051	0.064
	(0.232)	(0.249)	(0.220)	(0.246)
Research & Development	0.147	0.058	0.044	0.061
	(0.354)	(0.233)	(0.205)	(0.240)

3.4 Empirical model

To investigate how workers commuting behaviour changed in response to the pandemic, we start by estimating a model that interacts remote work potential with temporal variables in the following:

$$y_{it} = \beta_0 + \lambda Wfh_{it}^{p} + \delta Covid + \gamma (Wfh^{p} \times Covid)_{it} + \beta x_{it} + \mu_{it} + \tau + \varepsilon_{it} \quad (2)$$

where y_{it} denotes an indicator coded one if an employee i switches commuting status at time t to become a long-distance commuter defined by Eq. (1), WfH_{it}^{p} denotes the occupational index of remote work potential and $Covid$ include year dummies to indicate the pandemic years, 2020, 2021. The influence of WfH_{it}^{p} on the likelihood that an employee switches to long-distance commuting during the pandemic is given by γ, and λ can be interpreted as the influence of WFH potential on the likelihood to switch in pre-pandemic years. The model includes socioeconomic and demographic controls at the individual level, family and regional controls (x_{it}). The model further includes individual fixed-effects (μ_{it}) and year dummies (τ) to account for unobserved heterogeneity in preferences, abilities and time trends. We take several additional measures to reduce selection. The dependent variable only comprises the new long-distance commuters to account for previous experience (Sandow and Lundholm, 2020). We also include regional, industry and occupational fixed-effects using 2-digit SNI and occupational groups (SSYK). This allows us to exploit the influence of WFH potential within the same industry and occupational type, thereby also reducing biases related to occupational choice (Arntz et al., 2022).[2]

In a second step, we examine the robustness of our main findings for WFH potential with regard to the inclusion of covariates that indicate varying exposure to remote work during the pandemic. Specifically, we estimate a separate model for the pandemic years to contrast workers with jobs in the private vs. the public knowledge-intensive sectors and examine if (implied) varying exposure to remote work during the pandemic influenced the probability to switch commuting status. The second model has the following specification:

$$y'_{it} = \beta'_0 + \gamma' Wfh_{it}^{p} + \gamma'(Wfh^{p} \times Sector)_{it} + \beta' x_{it} + \mu_{it} + \tau + \varepsilon_{it} \tag{3}$$

where y'_{it} takes the value one if an employee switches to long-distance commuting after the start of the pandemic. The remaining variables, WfH_{it}, x_{it}, τ, are defined according to Eq. (2) with the difference that the model lifts the $Covid_{t=2020,2021}$ variable out and we instead interact WFH potential with a different "treatment", namely whether the occupation is in the public knowledge-intensive sector. Our conjecture is that many public sector workers have been much less exposed to distance work before the pandemic compared to during the pandemic (NAO, 2023). Presumably, then, the treatment implied by the WFH variable ought to have been more potent in this industry. As we argue above, there is an implied "under-exposure" to WFH in the public sector, pre-pandemic, which should induce public/government sector employees to alter their lengths of commutes relative more than the reference group (private sector), where the exposure has been more even.

[2] The LPM model is often used in favor of the logistic regression model in cases when data contains rare events (Timoneda, 2021).

4. Results

Table 3 shows the results from estimating the model (Eq. 2) in five specifications for the sample containing all employees across occupations (N=900,873) with last column results representing the fully specified model. The outcome variable is binary and takes the value one if an employee switches to become a long-distance commuter (50 km+) in a given year. As noted, this is often used as a minimum threshold based on the assumption that it approximates the maximum limit of time that the vast majority of workers are willing to spend on commuting one way (Johansson et al., 2002). The coefficient of the interaction term (γ) is positive and statistically significant throughout the estimations $(p < .01)$ indicating that WFH potential significantly increases the probability of switching to long-distance commuting during the pandemic. The coefficient of the variable WfH_{it} is however not statistically significant in the fully specified model and we cannot verify that WFH potential influences the likelihood to start longer commutes in pre-pandemic years. This result supports our conjecture that it is exposure to remote work that caused the substantial increase in new long distance commutes during the pandemic. Re-estimating the models including also those with previous experience of such commuting, the coefficient of WfH_{it} turns positive and statistically significant (Table S3). We arrive at a similar result $(\lambda = 0.022;\ p < 0.01)$ when we re-estimate the fully specified model using the continuous workplace-residential distance as the outcome (Table S4). This shows that our approach to consider only the new long-distance commuters is important in reducing selection effects.

Taken together, we find evidence that employees with presumably very little (or zero) previous experience of long-distance commuting before the pandemic were more likely to start longer commutes if they had occupations with high WFH potential. This estimate is robust to the inclusion of key socioeconomic controls (education level, income, family situation) and job type controls (job position and extent of work), as well as to regional, industry and occupational fixed-effects.

Table 3. Regression results: the influence of WFH potential on the probability of an employee switching to long-distance commuting before and during the pandemic

	(1)	(2)	(3)	(4)	(5)
Wfh^p	-0.0003	-0.0001*	-0.0006***	-0.00005*	-0.00009
	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
$Wfh^p \times Covid_{t=2020,2021}$	0.004***	0.005***	0.005***	0.004***	0.004***
	(0.0001)	(0.001)	(0.0001)	(0.0001)	(0.0001)
$Covid_{t=2020,2021}$	0.009**	-0.0004	-0.001**	0.003***	0.0008*
	(0.0001)	(0.0003)	(0.0002)	(0.0003)	(0.0003)
Age (ln)		0.071***	0.076***	0.126***	0.088***
		(0.003)	(0.002)	(0.003)	(0.003)
Income (ln)		0.002***	0.002***	0.003***	0.002***
		(0.0003)	(0.0001)	(0.0003)	(0.0003)
Full time employee		-0.009***	-0.010***	-0.009***	-0.008***
		(0.0001)	(0.0001)	(0.0001)	(0.0001)
University		0.003**	0.003***	0.002*	0.003**
		(0.001)	(0.0001)	(0.001)	(0.001)
PhD		0.019***	0.019***	0.017***	0.021***
		(0.001)	(0.001)	(0.003)	(0.003)
Single no children			-0.002***	-0.002***	-0.003***
			(0.0001)	(0.0003)	(0.0002)
Married/cohabitated (children < 5y)			-0.0002**	-0.0004***	-0.0001
			(0.0001)	(0.0002)	(0.0001)
Married/cohabitated (no children)			0.002***	0.001***	0.001***
			(0.0001)	(0.0002)	(0.0001)
Family income (ln)			0.003***	0.001***	0.001***
			(0.0003)	(0.0001)	(0.0001)
Residential relocation				0.018***	0.017***
				(0.0002)	(0.0002)
Dual homeownership				0.0002	0.0002
				(0.0003)	(0.0002)
Urban/Metro home				-0.066***	-0.057***
				(0.003)	(0.002)
Urban/Metro workplace				0.052***	0.054***
				(0.0003)	(0.0003)
House price (municipality)				-0.031***	-0.010***
				(0.001)	(0.001)
KI-ICT				-0.003	
				(0.0005)	
KI-Business Services				0.008***	
				(0.001)	
KI-Financial Services				0.005	
				(0.005)	
KI-Public Administration				0.005***	
				(0.0001)	
Individual FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Industry FE	No	No	No	No	Yes
Regional FE	No	No	No	No	Yes
Constant	-0.003***	-0.301***	-0.319***	-0.252***	-0.462***
	(0.0001)	(0.010)	(0.008)	(0.003)	(0.015)
R sq.	0.005	0.010	0.010	0.023	0.050
Obs.	5 932 134	5 932 134	5 934 134	5 934 134	5 934 134

Note: Linear probability model estimates with standard errors clustered at the individual level. Family income is set to zero for individuals without family members in the household. All equations have been estimated with occupational fixed effects and with controls for non-linear effects (age squared, income squared), capital income and the WFH potential of the spouse. Regression results excluding the interaction term are displayed in Table S2. $*\ p < .10$, $**\ p < .05$, $***\ p < .01$.

A central assumption in theories on the mobility impacts of the pandemic is that new work arrangements and technologies put in place during (and before) the pandemic enabled workers to rethink and adjust their commuting behaviours in favour of longer distances (Delventhal et al., 2022; Kyriakopoulou and Picard, 2023). We should thereby expect the influence of WFH potential on the probability to switch to be greater in magnitude during the second pandemic year compared to the first as experience and learning from WFH ought to be higher. Re-estimating the models with interaction terms that consider the two pandemic years separately, we find the interaction term to be greater in magnitude during the second pandemic year ($\gamma = 0.004;\ p < .01$) compared to the first ($\gamma = 0.002;\ p < .01$). This suggests that the probability to switch increases with exposure to remote work, which further strengthens the interpretation of our main results.

Table 4. Regression results: the influence of WFH potential on the probability of an employee switching to long-distance commuting during the *two* pandemic years

	(1)	(2)
WFH	0.00004 (0.0003)	
$WFH \times Covid_{t=2020}$	0.002*** (0.0001)	
$Covid_{t=2020}$	0.003*** (0.0005)	
WFH		0.00002 (0.0003)
$WFH \times Covid_{t=2021}$		0.004*** (0.0001)
$Covid_{t=2021}$		0.036*** (0.0007)
Constant	-0.390*** (0.018)	-0.395*** (0.018)
Individual FE	Yes	Yes
Year FE	Yes	Yes
Industry FE	Yes	Yes
Regional FE	Yes	Yes
R sq.	0.048	0.048
Obs.	5 934 134	5 934 134

Note: Linear probability model estimates with standard errors clustered at the individual level. The estimated models includes all the controls of the fully specified model. $*\ p < .10$, $**\ p < .05$, $***\ p < .01$.

4.1 Robustness of results regarding exposure to remote work

Table 4 shows the results of estimating Eq. (3) considering only the pandemic years, i.e., 2020, 2021 including those employed in knowledge-intensive sectors, to obtain a more narrow set of comparable employees. Estimating the model, we distinguish high-skilled workers with employments in non-local government sectors to contrast them with high-skilled workers in private sectors. The rationale is to investigate if (implied) varying exposure to remote work during the pandemic influenced the probability to increase commutes. Results show that the interaction term is positive and significant suggesting that those with jobs in the non-local government sector were associated with a higher probability to switch to longer commutes during the pandemic, compared to the reference group. The results are—again—consistent with the view that exposure to remote work increases the probability to start commuting longer to work. We perform additional robustness tests to confirm the main results. All the models were re-estimated using a different cut-off point for the distance threshold, including only those that switched to commutes longer than 70+ km (Sandow, 2010). Results remained essentially the same with a slight decrease in the significance of the interaction term reflecting WFH potential ($p<0.05$). The influence of WFH potential may materialize through the uptake of new work arrangements and technologies (Barrero et al., 2021; Adams-Prassl et al., 2022; Davis et al., 2024), but it may also be the result of different dynamics. Although results are robust to the inclusion of industry and occupation fixed-effects, occupations that allow for WFH may have different wage developments, which could be due to demand shocks (Ramani et al., 2021). We investigate if this influences results by accounting for wages at the occupational level using data on monthly wages (Statistics Sweden). The main estimates remain largely unaffected when controlling for the changes in occupation average wages over time (Table S5).

Results regarding socioeconomic and demographic controls are broadly aligned with those in studies that examine who are the long-distance commuters, pre-pandemic. We confirm the common finding that higher education and earnings are closely tied to long commutes (Dargay and Clark, 2012). Furthermore, and although we do not focus explicitly on the destinations of those that switched to long commutes, results show that the probability to switch is higher among those that have their residential location in urban municipalities (compared to rural), and among those that work in metropolitan municipalities (compared to rural and urban). This can be related to the evidence presented in Andersson et al. (2018) on Swedish long-distance commuters in pre-pandemic years. They found employees living in rural areas (and being recent migrants) to be associated with longer commutes. They also show that the commute distance of recent migrants and individuals who moved to rural areas have the longest commute distances. From our results, we note however that employees were more likely to switch to long-distance commuting following a move compared to the reference (change in workplace), this is robust across estimations.

Table 5. Regression results: the probability of an employee in knowledge-intensive industry to switch to long-distance commute during the pandemic

Wfh^{p}	-0.00003
	(0.0009)
$Wfh^{P} \times KI\_public$	0.002***
	(0.0009)
KI_public	-0.008**
	(0.0005)
Age (ln)	-0.001*
	(0.0007)
Gender (male=1)	0.0004*
	(0.0002)
Income (ln)	0.002***
	(0.0003)
Full time employee	-0.013***
	(0.0006)
University	0.0006
	(0.0003)
PhD	0.002**
	(0.0009)
Single no children	0.006**
	(0.002)
Married/cohabitated no children in household	0.0001
	(0.0002)
Married/cohabitated children < age 5 in household	-0.002***
	(0.0003)
Family income (ln)	0.002***
	(0.0001)
Residential relocation	0.042***
	(0.0001)
Dual homeownership	-0.002
	(0.003)
Urban/Metro home	-0.021***
	(0.001)
Urban/Metro workplace	0.023***
	(0.0002)
House price (municipality)	-0.005***
	(0.0003)
Year 2021	0.003***
	(0.0002)
Constant	0.026***
	(0.005)
R sq.	0.030
Obs.	452 573

Note: Linear probability model estimates with robust standard errors. Equations are estimated for the sample of employees with jobs in the knowledge-intensive private and public sectors defined in Table 1. The model has been estimated both with fixed effects (individual, occupation, region) and without with comparable main results. $*\ p < .10$, $**\ p < .05$, $***\ p < .01$

5. Conclusions

There is an ongoing debate in the scientific literature, as well as in policy circles, on the possible impacts associated with the major shift to remote work following the pandemic. A key question is whether this could lead to substantial and lasting effects on labour mobility and workers commuting behaviour. This study is one of the first to examine how exposure to distance work affects the decision to switch to long-distance commuting during the pandemic lockdowns. The analysis is based on detailed population-wide microdata over the period 2015–2021. Of particular interest are the group of employees who had no (or very little) experience of long-distance commuting in pre-pandemic years but decided to switch to such commuting after the start of the pandemic. This focus is a contribution to the literature, as previous studies have mainly examined who are the long-distance commuters in pre-pandemic years (Sandow, 2014; Andersson et al., 2018). The results of this study are consistent with predictions that we should expect more long-distance commuting in sectors and occupations with high skill-level and potential to work from home. We contribute to a growing literature on how the pandemic has altered workers mobility choices and how working from home affects the length of the commutes. Increasing attention is given to the notion that working from home is probably here to stay (Smite et al., 2023), which makes the possible effects on the geography of labour markets and job accessibility crucial to understand. Considering how remote work potential affects the length of the commute can inform policies aimed at improving the economic performance of cities and regions. A key takeaway from our study is that workers in knowledge-intensive occupations, and occupations with both high and low pre-existing share of working from home, may have larger local labour markets now compared to before the pandemic.

The findings in this study suggest that changing work arrangements during the pandemic have enabled employees with occupations that can be done from home to alter their commuting behaviors in favor of longer commutes, i.e. to combine work from home with long-distance commuting to their workplace. Unfortunately, data availability does not allow us to evaluate if the results presented in this study reflect permanent changes, that is, if they prevail post 2021, but the abovementioned report from Sweden's Engineers shows that for their members, the trend has continued up to 2024. More studies of this are of course necessary.

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Supplemental file

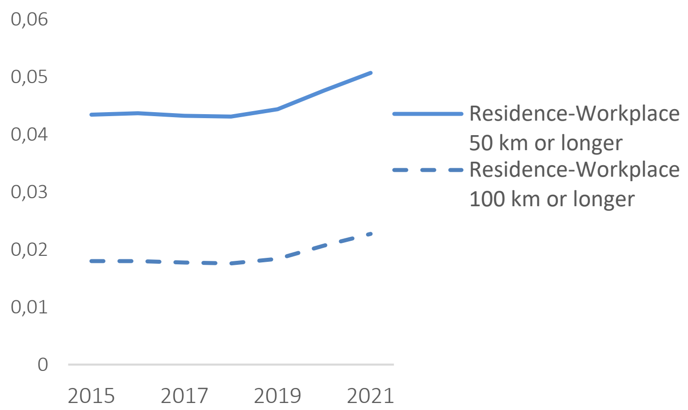

Fig S1. Share of employees in the sample that commute longer distances to work (50+ km and 100+ km) during 2015-2021.

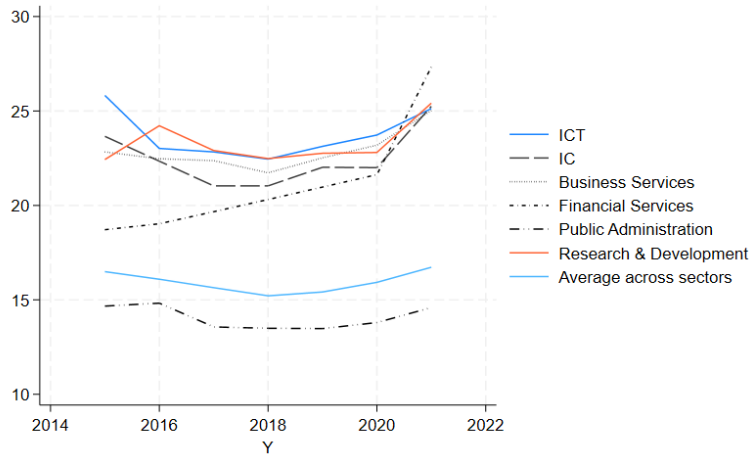

Fig S2. Mean residence–workplace distance in kilometres among employees across industries before and during the pandemic 2015-2021.

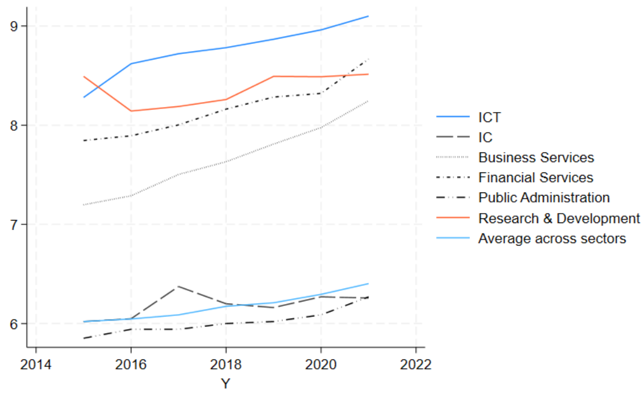

Fig S3. Median residence–workplace distance in kilometres among employees across industries before and during the pandemic 2015-2021.

Table S1. Variable definitions

Variable	Definition
y_{it}	Binary outcome variable equals one the year an employee becomes a long-distance commuter (50+ km) defined by Eq. (1), zero otherwise.
WfH potential	Index of working from home potential calculated using 3-digit occupational codes (SSYK 2012) and the occupational classification developed in Sostero et al. (2023).
Age	Age (logarithm).
Gender (male=1)	Equals one if male, zero otherwise.
Income	Income (logarithm).
Full-time employee	Equals one if the number of months of employment during the year equals 12, zero otherwise.
Family income	Income of household members (logarithmic) indicating dual-earner households (Clark et al., 2003). Does not include the individual income and set to zero if employees is single in the household.
University	Equals one if the highest level of education is university (at least 3 years), zero otherwise.
PhD	Equals one if the highest level of education is PhD, zero otherwise (university and PhD are mutually exclusive).
Managerial position	Equals one if job position is managerial/executive, zero otherwise. Calculated using 3-digit occupational codes (SSYK3 2012, 112-179).
Single no children	Equals one if single and no children in household, zero otherwise.
Married/cohabitated no children	Equals one if married or cohabitated with no children in the household, zero otherwise.
Married/cohabitated children < 5 years	Equals one if married or cohabitated with children under the age of 5 years in the household, zero otherwise.
Residential change	Equals one if the employee changed residential location (moved) in year t or $t-1$ keeping the same workplace location, zero otherwise (the reference category consists of employees that changed workplace in year t or $t-1$ keeping the same residence).
Urban/Metro residence	Equals one if the residential municipality is urban or metropolitan (base rural), zero otherwise.*
Urban/Metro workplace	Equals one if workplace municipality is urban or metropolitan (base rural), zero otherwise.
House price	Average price of single homes in municipality.
Dual homeowner	Equals one if an employee owns more than one single home (including vacation homes), zero otherwise. Constructed using information from the Swedish Property Tax Registry (FPR).
KI-industry private	Equals one if the industry of occupation is in private knowledge-intensive sector (ICT, IC, Business Services, Financial Services), zero otherwise.
KI-industry public	Equals one if the industry of occupation is public knowledge-intensive sector (Public Administration, Higher Education), zero otherwise.

Notes: *Urban region:* Municipalities with a population of at least 30 000 inhabitants, where the largest city has a population of 25 000 people or more. In practice, this group is basically composed of the metropolitan areas, regional centers and their “suburb municipalities”.*Rural regions:* Municipalities not included in the urban areas are classified as rural regions.

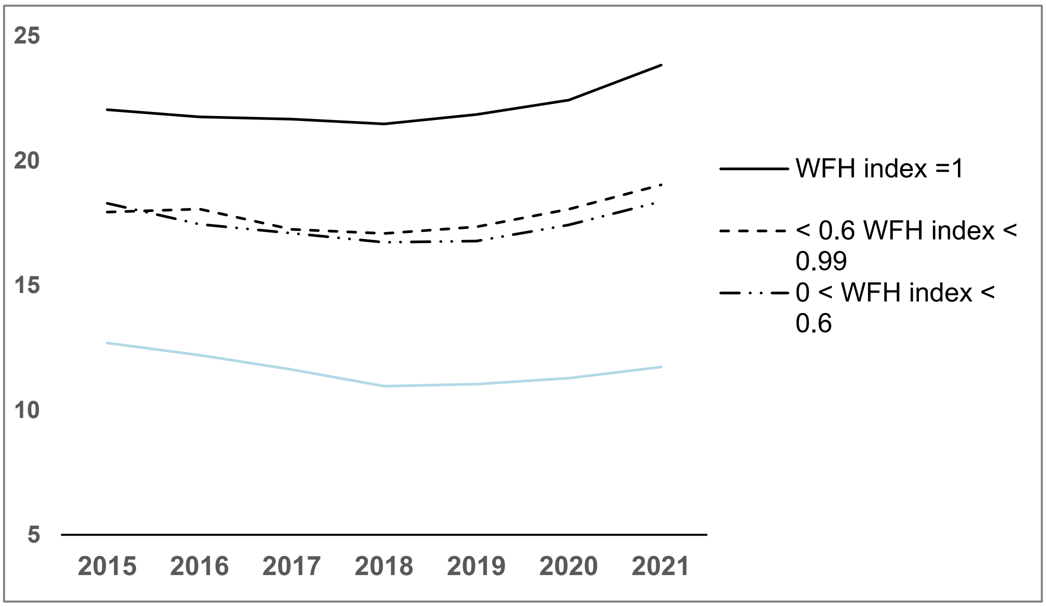

Fig S4. Graphical illustration of WfH classification index used in this study (Sostero, 2023) applied to our sample of employees with workplace-residential distance in kilometres on the y-axis.

Table S2. Regression results: excluding the interaction term.

WfH	0.0008*** (0.0003)
$WfH \times Covid_{t=2020,2021}$	-
$Covid_{t=2020,2021}$	0.0025** (0.0003)
Constant	-0.452*** (0.012)
Individual FE	Yes
Year FE	Yes
Industry FE	Yes
Regional FE	Yes
R sq.	0.047
Obs.	5 932 134

Note: standard errors clustered at the individual level. The estimated model contains the socioeconomic, demographic and regional controls of the fully specified model in Eq. (2).
$* \, p < .10$, $** \, p < .05$, $*** \, p < .01$.

Table S3. Linear probability model estimates for the sample including employees with previous experience of long-distance commuting.

WfH	0.003*** (0.0001)
$WfH \times Covid_{t=2020,2021}$	0.005*** (0.0001)
$Covid_{t=2020,2021}$	0.002** (0.0001)
Constant	0.674*** (0.239)
Individual FE	Yes
Year FE	Yes
Industry FE	Yes
Regional FE	Yes
R sq.	0.049
Obs.	6 224 440

Note: standard errors clustered at the individual level. The estimated model contains the socioeconomic, demographic and regional controls of the fully specified model in Eq. (2).
$* \; p < .10$, $** \; p < .05$, $*** \; p < .01$.

Table S4. Linear fixed effects estimates for the sample of all employees using the log of the continuous workplace-residential distance as the dependent variable.

WfH	0.022*** (0.002)
$WfH \times Covid_{t=2020,2021}$	0.013*** (0.001)
$Covid_{t=2020,2021}$	0.012*** (0.003)
Constant	0.674*** (0.239)
Individual FE	Yes
Year FE	Yes
Industry FE	Yes
Regional FE	Yes
R sq.	0.043
Obs.	6 243 920

Note: Standard errors clustered at the individual level. The estimated model contains the socioeconomic, demographic and regional controls of the fully specified model in Eq. (2).
$* \; p < .10$, $** \; p < .05$, $*** \; p < .01$.

Table S5. Linear probability model estimates controlling for changes in occupation average wages over time

WfH	-0.00006 (0.0003)
$WfH \times Covid_{t=2020,2021}$	0.004*** (0.0002)
$Covid_{t=2020,2021}$	0.0006* (0.0002)
Occupational wage	0.024*** (0.006)
Constant	-0.461*** (0.015)
Individual FE	Yes
Year FE	Yes
Industry FE	Yes
Regional FE	Yes
R sq.	0.049
Obs.	5 934 134

Note: standard errors clustered at the individual level. The estimated model contains the socioeconomic, demographic and regional controls of the fully specified model in Eq. (2).
$* \; p < .10$, $** \; p < .05$, $*** \; p < .01$.