Coskun, Sena; Dauth, Wolfgang; Gartner, Hermann; Stops, Michael; Weber, Enzo

Working from home increases work–home distances

Date of secondary publication: 13.02.2026

Version of Record (Published Version), Article

Persistent identifier: urn:nbn:de:bvb:473-irb-113167x

Primary publication

Coskun, Sena; Dauth, Wolfgang; Gartner, Hermann; u. a. (2026): Working from home increases work–home distances, in: Journal of urban economics, Amsterdam: Elsevier, Vol. 152, No. 103832, pp. 1–12, doi: 10.1016/j.jue.2026.103832.

Journal of Urban Economics 152 (2026) 103832

Contents lists available at ScienceDirect

Journal of Urban Economics

journal homepage: www.elsevier.com/locate/jue

Working from home increases work–home distances[☆]

Sena Coskun [a,b], Wolfgang Dauth [b,c,*], Hermann Gartner [b,a], Michael Stops [b], Enzo Weber [b,d]

[a] FAU Erlangen–Nuremberg, Germany
[b] Institute for Employment Research (IAB), Germany
[c] University of Bamberg, Germany
[d] University of Regensburg, Germany

ARTICLE INFO

JEL classification:
J61
R23

Keywords:
Working from home
Commuting
Urban labor markets

ABSTRACT

This paper examines how the increased acceptance of working from home during and after the Covid-19 pandemic shapes how labor market and locality choices interact. We combine large administrative data on employment biographies in Germany and a new working from home potential indicator based on comprehensive data on working conditions across occupations. We find that, in the wake of the pandemic, the distance between workplace and residence has increased more strongly for workers in occupations that can be done from home: The association of working from home potential and work–home distance increased significantly since 2021 as compared to a stable pattern before. The effect is much larger for new jobs, suggesting that people match to jobs with high working from home potential that are further away than before the pandemic. Most of this effect stems from jobs in big cities, which indicates that working from home alleviates constraints by tight housing markets. We find no significant evidence that commuting patterns changed more strongly for women than for men.

1. Introduction

The decision of workers to commute between their place of residence and their workplace crucially determines the functioning of labor markets. In particular, commuting enables workers to disentangle the place of residence and the place of work to a certain extent. However, the time spent commuting is neither productive, nor can it be used for recreation or household duties. Search models where commuting matters (e.g., Van den Berg and Gorter, 1997) therefore postulate that workers expect to be compensated for a longer commute by earning higher wages. This is possible since commuting increases the probability that workers can be employed at high paying establishments and also the probability that workers find jobs that match their specific skills (Dauth and Haller, 2020). Commuting is also beneficial from an aggregate perspective. The probability that workers and firms form productive matches increases with the size of the local labor market (Dauth et al., 2022). This can either be achieved by workers moving into a local labor market or by workers extending their search radius and therefore increasing the number of possible employers they could reach from their residence. Accordingly, matching efficiency and employment would increase with the effective size of the local labor markets, as simulated in Wolter et al. (2021).

The aim of this paper is to examine how the increased acceptance of working from home (WFH) in the wake of the Covid-19 pandemic has affected commuting behavior. The possibility to telecommute reduces the necessary number of commutes and therefore the costs per kilometer between residence and workplace. Other things equal, we therefore expect an increase in this distance after working from home has become more widely accepted. While WFH used to be rather an exception before the pandemic, investment into the digital infrastructure of firms, new standards for operational processes, as well as communication and relevant technological innovations have made WFH comprehensively accepted by employers (Bloom et al., 2021) and a widespread requirement from the workers' side. For example, Kagerl and Starzetz (2023) report that the share of German establishments enabling WFH has risen from 25 percent in 2019 to roughly 50 percent in January 2021 and has remained at this level at least until June 2022. Individuals have

☆ Acknowledgments: We thank the editor, Nathaniel Baum-Snow, two anonymous reviewers, Sebastian Findeisen, Miquel-Àngel Garcia-López, and Milan Quentel, as well as participants of the 2024 Remote Work Conference in Stanford, the 2025 UEA Meetings in Berlin, and the BIR workshop 2025 in Bonn for their very constructive feedback. We also thank Udo Brixy, IAB's DIM department, and the IT department of the German Federal Employment Agency (BA) for computing the precise work–home distances for us. Any remaining errors are ours. The replication archive for this paper is available at Coskun et al. (2026).

* Corresponding author at: Institute for Employment Research (IAB), Germany.
E-mail addresses: sena.coskun@fau.de (S. Coskun), wolfgang.dauth@iab.de (W. Dauth), hermann.gartner@iab.de (H. Gartner), michael.stops@iab.de (M. Stops), enzo.weber@iab.de (E. Weber).

https://doi.org/10.1016/j.jue.2026.103832
Received 10 April 2024; Received in revised form 9 January 2026
Available online 22 January 2026

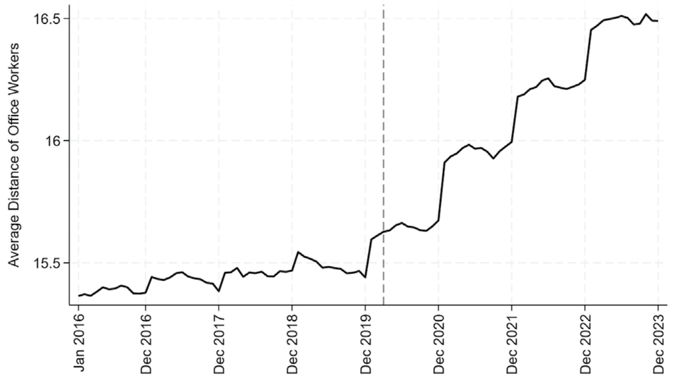


Fig. 1. Evolution of work–home distances for office workers.
Notes: The figure reports the average work–home distances of workers in office jobs (all occupations with a KldB 2010 code that starts with 7). Distances are calculated as the linear distances between the individuals' places of residence and of work, the censored distances above 200 km are imputed by distances between the geographic centers of the municipalities of residence and of workplace. For continuous employment, employers report data only once a year, which causes discrete changes in January, in addition to the changes that actually occur at the beginning of the year.
Source: 2% random sample of the Integrated Employment Biographies (IEB) provided by the German Institute for Employment Research (IAB). BERUFENET. Own computations.

reacted to this development. For example, the occupations with the highest potential to be done remotely and with the most inflows of job changers include office clerks and secretaries, occupations in business organization and strategy, and occupations in accounting, controlling and auditing.

In this paper, we study if and how German employees have reacted to the increased acceptance of WFH. Did work–home distances increase with regional restrictions relaxed by more widespread WFH options? Is that due to the take-up of different jobs or due to relocation of the residence? Are the changes related to differences in housing costs? Can more peripheral regions with lower rent levels attract individuals to live there and, at the same time, to take up or keep jobs in metropolitan areas?

Indeed, Fig. 1 suggests that work–home distances of workers in office jobs have strongly increased in the wake of the Covid-19 pandemic, arguably due to the increased acceptance of WFH. There was a secular trend of increasing work–home distances already before the pandemic, most likely due to rising housing costs in big cities, where those jobs are concentrated. This trend stagnated in 2019 but accelerated significantly in the beginning of 2021. Office workers are likely to work from home for at least a part of their workweek. Other occupations, by contrast, require physical contact and therefore workers need to commute to their work every day. In this paper, we exploit the heterogeneity of how well occupations are suited for remote work to identify the effect of the increased acceptance of WFH on work–home distances.

We regard the corona shock as a natural experiment that affected different occupations differently according to their suitability to WFH. We define this WFH potential as the possibility to perform an occupation remotely. For this purpose, we use the Home Office Potential (HOP) indicator, proposed by Bruns et al. (2025). This new measure is based on the occupational data base BERUFENET, the German equivalent to O*Net. HOP is defined as the share of an occupation's working conditions (rather than tasks) that enable mobile work. The construction of HOP does not rely on the actual use of WFH—unlike the indicators by Alipour et al. (2023) or Arntz et al. (2020)—thus, making the indicator less vulnerable to endogeneity issues. 30.3 per cent of all observations in our data have occupations in the upper quartile of the distribution of HOP values at the occupation level. This share is comparable to the share of 30.9 percent reported by Arntz et al. (2020) for "fully teleworkable" jobs; Dingel and Neiman (2020) report a slightly larger share of around 36 percent of German jobs "that can be done at home". By contrast, Alipour et al. (2021) report a share of 56 percent but rely on a measure that is binary and not continuous as ours.

We combine the data on WFH potential with large administrative data on employment biographies in Germany. This allows us to analyze a broad set of outcomes such as precise work–home distances, labor market transitions, job characteristics, wages, unemployment spells, and relocation over time and during the pandemic. Our results show that the association of WFH potential and work–home distance increased significantly since 2021 as compared to a stable pattern before. The effect of the realization of WFH potential since 2021 is much larger for new jobs, suggesting that people match to jobs with high WFH potential, which are further away than before the pandemic. In 2023, the average distance between place of residence and workplace was 36 km greater for employees who started a job suitable for WFH than for one not suitable — while before the pandemic, it was 19 km. The change is mainly driven by workers with home office potential in the upper quartile. For existing jobs we find a smaller but still significant positive effect of 7 km on work–home distance. Apparently, at least some people with high WFH potential have relocated their residences to places further away.

We then focus on the mechanisms behind the rising home–work distance. First, we conduct a decomposition exercise and show that the largest share of this increase can be explained by workers who do not move their residence but switch to new jobs with a high HOP that are further away. Second, we split our data by whether the initial residence locations were in big cities, close to big cities, or further away, and look more closely at the subsequent residential and workplace decisions. Our findings imply that the geographic scope of labor markets around big cities has expanded. However, this tendency attenuates with increasing distance from the cities. We find that individuals working in big cities are more likely to live in the surrounding areas of those big cities but not in very remote regions. Apparently, the requirement of hybrid WFH arrangements to still be at the workplace for a fraction of the workweek prevents the majority of workers to fully disentangle workplace and residence locations. Furthermore, we find that the rent prices, measured consistently in pre-pandemic prices, at the residence of people in high HOP jobs decreased by 0.6% while the rent prices at the firms location increased by 0.2%, as compared to people in low HOP jobs. This means that jobs were located in more expensive regions than before, but workers chose cheaper regions to live. While WFH offers the potential to reduce the gender commuting gap, we find no significant evidence that commuting patterns changed more strongly for women than for men. If anything, the difference between housing prices at the workplace and the place of residence has increased more strongly for men.

Our study contributes to several strongly developing strands of literature. There are already many papers on the prevalence and effects of working from home during and after the COVID-19 pandemic. The development of WFH in the United States is, e.g., documented by Barrero et al. (2023) or Bick et al. (2023). The literature highlights several key dimensions: The impact of WFH on productivity is analyzed by Atkin et al. (2023). Based on an experimental design, they find that productivity is significantly lower when working from home compared to the office.

Lei (2024) finds that the reduced importance of geographic constraints has influenced labor market concentration in the U.S. By considering remote jobs as relevant to all local labor markets, the degree of vacancy concentration across firms decreases. Similarly, Liu and Su (2024) argue that WFH increases labor supply for urban jobs, thereby reducing the urban wage premium especially for interpersonal skills. Both studies, using job advertisement data, analyze new matches but do not examine changes in work–home distances for existing job matches.

Furthermore, WFH has gender-specific implications: Boll et al. (2024) suggest that increased flexibility for fathers may lead to a more equitable childcare division, thereby expanding women's job search opportunities. Their analysis, based on household survey data, focuses on labor division within families rather than worker–firm matches. Monte et al. (2023) investigate the effects of the COVID-19 shock on WFH and commuting, with a focus on intra-city patterns. However, their study does not consider commuting between cities or rural areas.

In addition to the literature on WFH, since the pandemic, a large body of research has developed analyzing the shift in residential location choices. Ilham et al. (2024) provide a recent review along dimensions such as trip patterns, modal shifts, teleworking and activity shifts, the influence of online shopping, location and dwelling preferences as well as digital connectivity. Recent studies have regularly identified changes in mobility behavior, choice of residence, and WFH prevalence that occurred in parallel during the pandemic. A phenomenon that is observed in a number of different countries has been dubbed the "donut effect" (Ramani et al., 2024): While the possibilities offered by WFH allow households to move from big cities to less dense places, the necessity to still commute to the workplace on a regular basis has directed relocation patterns towards the suburbs of those cities rather than towards truly remote locations. Brueckner et al. (2023) show that this has an impact on the house price gradient in cities: Since access to the central business district became less important, the relationship of home prices and distance to the center has become flatter.

Despite these insights, little is known about the impact of WFH on concrete work–home distances and location choices. Our study addresses this gap. A related study is Akan et al. (2025). They use matched employer–employee data from a private company for management services and find that the share of long-distance commuters has strongly increased since the pandemic. Their data allows them to observe details on working arrangements, however the group of establishments using the company's services is highly selective. Furthermore, they present more descriptive results, whereas we use a difference-in-differences approach to identify the effects the realization of WFH potentials due to the corona shock. A key advantage of our data is its comprehensive coverage of the locations of workers and establishments across the entire German economy with longitudinal information. We investigate how work and residential locations have adjusted jointly. In particular, analyzing both new job matches and ongoing employment relationships allows us to track changes in job locations as well as changes in workers' residences.

The paper is structured as follows. Section 2 expounds how the increased acceptance of WFH increases the reservation radius of job seekers and formulates hypotheses how this affects individual decisions on residence and workplace locations. Section 3 introduces the administrative labor market data and the construction of the HOP indicator. Section 4 discusses our research design, and Section 5 presents the estimation results. The last section concludes.

2. Conceptual background

To motivate our empirical analysis, we consider a simple monocentric-city model in which workers choose residential locations at a distance X from their workplace in the city center. Workers derive utility from consumption of a composite good C and housing services H according to Cobb–Douglas preferences. They supply one unit of labor, e.g. a full work week, which includes the time required to commute to the workplace. They face the budget constraint $C + P(X)H = W(1 - t(X))$, where W is the wage rate, $t(X)$ the fraction of total time workers spend commuting, the price per unit of housing is $P(X)$, and the price of consumption is normalized to 1.

Solving the household's problem yields the indirect utility

$$\log U \approx \log W - t(X) - a \log P(X) + const \tag{1}$$

This expression shows the canonical trade-off in the monocentric city model: For the spatial equilibrium to hold, a longer commute must be compensated by lower unit housing prices. More precisely, workers choose their location X to maximize utility, which yields the internal equilibrium condition:

$$d(\log U) = 0 \quad \Rightarrow \quad -t'(X)\,dX - a\,\frac{P'(X)}{P(X)}\,dX = 0. \tag{2}$$

In an open monocentric city, the population of a city is determined by the relation of the utility from working in the city and the outside utility one could achieve elsewhere. This implies that, with a given wage and commuting costs per unit of distance, there is a certain reservation distance that delimits the city's commuting zone. To show how WFH enters this consideration, we assume that commuting time depends both on travel distance and on how often commuting occurs within the period:

$$t(X) = \omega\,\tau(X), \tag{3}$$

where $\tau(X)$ is the fraction of one working day that is needed to drive to the workplace and back and $\omega \in [0,1]$ represents the fraction of workdays within the reference period that an individual actually does commute. The possibility to work from home reduces the required number of commuting trips ω and therefore the commuting time $t(X)$ (which has been shown empirically by Aksoy et al., 2023). Deriving Equation (3) by X gives $t'(X) = \omega\tau'(X)$. Since $\tau'(X) > 0$, a reduction of ω must be compensated by an increase in $P'(X)$ in Eq. (2), which means that the housing price gradient becomes flatter. Intuitively, access to the central business district becomes less important while living further away is less unpleasant. Workers will therefore be willing to reside farther from their workplaces in the city center, thereby increasing their reservation distance. This mechanism provides two direct empirical predictions: The reduced need to commute daily results in (i) an increasing average distance between work and home locations and (ii) a flattening of the housing price gradient within a city. The latter has been documented by Brueckner et al. (2023) and the former will be the main focus of this paper's analysis.

Since our data does not allow us to observe the number of commuting trips or its reduction directly, we exploit the fact that not all jobs can be done remotely to the same extent. Plausibly, the share of days commuted (ω) is negatively related to the job's WFH potential. Put differently, the maximum distance workers are willing to commute should be positively related to how good their job is suited for WFH. Traditionally, however, the theoretical relationship between WFH potential and actual days worked from home has not been binding as working in the office used to be the norm even in jobs that could be done from anywhere. This changed profoundly during the Covid-19 pandemic, which created an exogenous shock to the acceptance of WFH, including technical and organizational prerequisites. We regard this as a natural experiment that creates variation in ω.

Several testable hypotheses can be derived from this consideration. First, we expect the average work–home distance to be positively related to the WFH potential. This relationship should be significantly stronger in the wake of the Covid-19 pandemic as only then the WFH potential could be realized. There are two margins of how workers could adjust their work–home distance: By switching residences and/or workplaces. The former relates directly to the model sketched above and was arguably more prevalent in the public perception, especially for residents of big cities. Social distancing reduced the value of urban amenities while free spaces and larger dwellings became more attractive. We therefore expect, second, to find that the increase in work–home distances is in part driven by workers who used to live and work in big cities before the pandemic and then relocate their residence outside of those big cities — but predominately if they work in occupations than can be done remotely. The other margin is switching to a different employer. Increasing WFH potential might mean that attractive jobs in the central business district now lie within the reservation distance of workers who used to work outside of those cities' centers (in other cities or in secondary business districts as described by Fujita and Ogawa, 1982). This leads to the fourth hypothesis that another significant part of the increasing work–home distances can be explained by individuals living outside the usual commuting zone of big cities taking up jobs with a high WFH potential at urban employers. In extreme cases of fully remote work, this could even be connected to very large distances.

3. Data

Sources. We obtain data on employment from a 2 percent random sample of the Integrated Employment Biographies (IEB v17.01.00-202312) provided by the German Institute for Employment Research (IAB).[1] The data comes from the social security system and covers 80 percent of the labor force (civil servants and self employed are not included). The data follows the individuals during periods of employment and unemployment on a daily base and provides information on education, occupation, wages, and other worker characteristics. In our analysis, we consider the years from 2016 to 2023. We constructed a monthly dataset to account for seasonality. The unit of observation is jobs. We excluded jobs when an individual worked less than 10 days in that job in a given month. In case a person has multiple jobs at the same time, we kept only the main job, that is the job with the highest tenure. We consider this as reasonable, since commuting to secondary jobs might entail mechanisms that are more complex compared to what we lay out in Section 2. However, keeping all jobs does not alter our results in any qualitative way.

The data includes the location of workers' residences and of the workplaces at the administrative level (approximately 11,000 local administrative areas called "Gemeinden"), which we henceforth refer to as municipalities. More importantly, the underlying raw data contains the exact coordinates of the place of residence and workplace for almost all observations in our dataset. We define the work–home distance as the direct linear distance between those coordinates.[2]

We rely on two data sources to capture the centrality of workplace or residence locations. First, we use the classification of counties of the Federal Institute for Research on Building, Urban Affairs, ans Spatial Development (BBSR).[3] This classification distinguishes between big cities with more than 100,000 inhabitants that form their own county, urbanized counties that mostly directly surround big cities, was well as rural counties, and sparely populated rural counties. Second, we utilize average rent prices at the county level provided by Mense et al. (2023) that stem from posted rent information on three large online real estate market places (Immonet, Immowelt, Immobilienscout24) on a monthly basis between July 2011 and December 2022.[4]

To describe each occupation's suitability to be performed remotely, we use the HOP indicator proposed by Bruns et al. (2025). The HOP indicator is complementary to other indicators proposed in the literature: firstly, the indicator does not rely on the actual use of WFH, like in Alipour et al. (2023, 2021), or Arntz et al. (2020); this makes HOP less vulnerable to endogeneity issues. Secondly, the indicator relies on comprehensive working conditions details rather than tasks to determine whether a job can be done from somewhere outside the workplace (like in Dingel and Neiman, 2020). The indicator is constructed based on detailed information on working conditions for each occupation from the expert data base BERUFENET[5] that provides information for (almost) all known occupations in Germany. Besides others, the working conditions for each individual occupation are reported at a very detailed occupational level; these individual occupations are organized in a 8-digit code framework that is fully compatible with the more aggregated systematic of the German classification of occupations 2010 (KldB 2010, compatible to ISCO-08) also utilized in our study.

Bruns et al. (2025) classified the working conditions allowing WFH (valued as 1), being "ambiguous" or "neutral" to WFH (0), or being more of a hindrance for WfH (−1). To calculate the HOP for each individual occupation, the total of the values for the working conditions is divided by the number of working conditions in each occupation. The resulting value can range between "−1" and "+1". After normalization the values of the resulting HOP indicator lie between 0 and 1, with a mean of 0.397 and a standard deviation of 0.222.[6] Further details, the result of a validity check based on data on the actual use of WFH, and further descriptive graphs that show the concentration of jobs with large HOP values in bigger cities are presented in Online Appendix A.

Descriptive statistics. Table 1 reports for all variables in our main analysis the mean, the standard deviation, the minimum and maximum values. For continuous variables, we additionally report the 25th, the 50th, and the 75th percentiles of the respective distribution. For example, we find an average distance of 27.35 km between the workplace and the home location, which varies between 0 km and 1088.55 km, with a standard deviation of 79.58 km. The median is only 7.8 km, which suggests that the distribution is skewed with few extreme values. The HOP indicator varies between 0 and 1 with a mean of 0.39.

Table 1 further shows that 36.49 per cent of job spells can be observed in Big Cities. Workers are, in average, 43.16 years old, 47.01 per cent of jobs are performed by female workers, and the average duration of an individual in the job is 82.32 months.

We now compare the pre- and post-pandemic values of some variables in June 2019 and June 2023. Table 2 shows that work–home distances increased by 3 km from 26.6 to 29.6 km. Remarkably, the share of individuals who commute within the big cities remained constant at 20.0 per cent and also the HOP indicator remained at 0.39.

4. Empirical strategy

In our empirical analysis, we seek to explore the role of WFH potential for work–home distances (as well as other outcomes). To illustrate the empirical strategy, assume that there are two industries; the first industry includes jobs with full and the second with no WFH potential. Further assume there is a single treatment date where the relevance of WFH increases for exogenous reasons. In such a setting, we can use classic difference-in-difference estimation. This isolates the change in distance for WFH jobs that goes beyond the change for no-WFH jobs.

The identification is based on the parallel trends assumption: The development of the outcome would not have differed between the

[1] This data set is very similar to the publicly available SIAB, which does not contain the very disaggregated information on locations and work–home distances we use in this study (for more details on SIAB see Schmucker et al., 2023).

[2] The coordinates are stored in the so-called "vault" at the German Federal Employment Agency (BA). While it is currently not possible to use the exact coordinates for research due to data security limitations, BA's IT department agreed to compute the distances using the Pythagorean theorem within the "vault", which are not sensitive from the perspective of data security regulations. The distances obtained by this process have been rounded to 100 m and winsorized at 200 km by BA's IT department. We impute the censored distances by using distances between the geographic centers of the municipalities of residence and of workplace.

[3] Source: https://www.bbsr.bund.de/BBSR/DE/forschung/raumbeobachtung/Raumabgrenzungen/deutschland/kreise/siedlungsstrukturelle-kreistypen/kreistypen.html; see Appendix Figure B.1 for a map of the county types.

[4] Since rent data is missing for the city of Amberg in North-Eastern Bavaria (with a population of around 42,000) we omit observations with this city as a workplace or place of residence, but only in the respective analyses.

[5] http://berufenet.arbeitsagentur.de.

[6] Bruns et al. (2025) also propose a second version of the HOP indicator that solely relies on the working condition "screen work", which we do not use in this study.

Table 1
Descriptive statistics of the analysis data set.

	Mean	sd	min	max	p25	p50	p75
Work–home distance	27.4	79.6	0.0	1088.6	2.9	7.8	17.6
HOP	0.39	0.23	0.00	1.00	0.19	0.31	0.61
Rent at work county (median)	562.58	182.72	245.42	1215.85	429.35	541.43	664.90
Rent at home county (median)	548.51	173.21	245.42	1215.85	424.53	530.22	647.00
Rent difference (Work–Home)	14.06	99.10	−954.63	954.63	0.00	0.00	0.00
Big city (work place)	0.36	0.48	0	1	–	–	–
Age	43.16	13.86	0	116	32	44	54
Female worker	0.47	0.50	0	1	–	–	–
Tenure in a job	82.3	79.6	1	300	17	52	131
Observations	66,546,735						

Notes: This table reports summary statistics of the data used in the regression analyses. The observation period is 2016–2023.

Table 2
Changes of main variables between June 2019 and June 2023.

	Mean	sd	min	max	p25	p50	p75
Distance (2019)	26.6	77.8	0.0	1038.0	2.9	7.7	17.4
Distance (2023)	29.6	85.0	0.0	1088.6	3.0	8.0	18.1
Within big city commuter (2019)	0.20	0.40	0	1	–	–	–
Within big city commuter (2023)	0.20	0.40	0	1	–	–	–
HOP (2019)	0.39	0.23	0.00	1.00	0.19	0.31	0.60
HOP (2023)	0.39	0.24	0.00	1.00	0.19	0.32	0.63
Observations (2019)	699,835						
Observations (2023)	707,780						

Notes: This table reports summary statistics of selected data to compare the pre- and post-pandemic values.

groups without the treatment. This can at least be made plausible considering the data for the pre-treatment period. Of course, in reality, the relevance of WFH for different occupations varies: Indeed, we observe the full range of the HOP indicator across occupations. Therefore, we follow the logic of difference-in-difference approaches but identify an effect of the shock by using a continuum of exposure. Thus, the treatment variable is not merely given by a dummy but by the WFH potential per occupation. Therefore, the procedure represents a difference-in-difference approach with continuous treatment intensity rather than binary treatment.[7] We also report the results for a standard difference-in-difference estimation with binary treatment variable.

Our main regression model is illustrated in Eq. (4). The outcome variable is d_{jt}, the commuting distance of individual j in a certain month and year, denoted by t. We proxy the fraction of days NOT commuted $1-\frac{\omega}{\Omega}$ by $HOP_{o(j,t)}$, the WFH potential of occupation o, held by individual j at time t. $HOP_{o(j,t)}$ is interacted with dummy variables indicating the number of months s relative to the onset of the Covid-19 pandemic in March 2020, which we define as $s = 0$.

$$d_{jt} = \gamma HOP_{o(j,t)} + \sum_{s=-50, s\neq 0}^{45} \left[\beta_s HOP_{o(j,t)} \mathbb{1}(t = s)\right] + \delta_t + \psi_{o(j,t)} + \phi_{s(j,t)} + \nu_{ind(j,t)} + \beta X_{jt} + \epsilon_{jt} \tag{4}$$

where δ_t is a vector of year-month fixed effects, $\psi_{o(j,t)}$ are 3-digit occupation fixed effects, $\phi_{s(j,t)}$ are federal state fixed effects, $\nu_{ind(j,t)}$ are industry fixed effects, ϵ_{jt} are the errors and X_{jt} includes controls: age, age square, gender, and tenure in the job.

The fixed-effect setting implies that we measure which difference in distances can be ascribed to WFH potential of different 5-digit occupations within the same 3-digit occupation, the same federal state and the same industry, controlled for personal characteristics. The coefficient γ reflects the expected difference in the base period March 2020. The interaction terms of HOP and month dummies allow that this relation between HOP and work–home distances can evolve over time. Those differences for the months during and after the Covid shock are given by $\beta_1, \beta_2, \ldots, \beta_{45}$, which represent the months April 2020 through December 2023. These coefficients measure the additional distance per unit of the HOP indicator realized in the relevant treatment period. This corresponds to the causal effect of the realization of WFH potential due to the increased acceptance of WFH in the wake of the pandemic.

The β-coefficients with negative subscripts represent the months from January 2016 through February 2020 and capture possible pre-trends. Note that estimating these coefficients involves full range of placebo tests. I.e., insignificant effects in periods without treatment will strengthen the assumption behind our identification. We account for the possibility that error terms are correlated for individuals who hold the same 5-digit-occupation (the source of variation of HOP) and within year–months by using the two-way clustered standard error option provided by Correia (2016).

In further analyses, we estimate a more parsimonious model as shown in Eq. (5). Here, we collapse the monthly interactions to the level of calendar years. β_{2020}, β_{2021}, β_{2022}, and β_{2023} represent the differential effects of the realization of WFH potential during and after the Covid-19 pandemic, relative to the time before the pandemic. In some models, we also use other outcome variables to examine further implications of the changing commuting behavior due to the increased practice of working from home.

$$d_{jt} = \gamma HOP_{o(j,t)} + \sum_{y=2020}^{2023} \left[\beta_y HOP_{o(j,t)} \mathbb{1}(year(t) = y)\right] + \delta_t + \psi_{o(j,t)} + \phi_{s(j,t)} + \nu_{ind(j,t)} + \beta X_{jt} + \epsilon_{jt} \tag{5}$$

5. Results

5.1. Main results

We start by examining the changing effect of the realization of WFH potential for every month between 2016 and 2023. Note that people who hold jobs with higher WFH potential have higher work–home distance on average (see Figure A.5 in the Online Appendix). This baseline tendency is captured by the variable $HOP_{o(j,t)}$ in Eq. (4). In

[7] See Callaway et al. (2024), for example, for a discussion on the differences between a binary and a continuous treatment variable. The latter approach has been used for example in the literature concerned with the measurement of the effects of a nationwide minimum wage on employment; see, for instance, Card (1992).

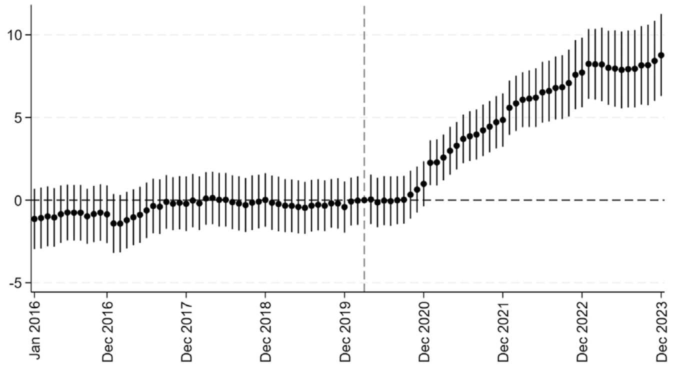


Fig. 2. Effect of the realization of WFH potential on work–home distance.
Notes: The figure reports the results of a regression of individual work–home distances on HOP, year–month-dummies and interactions of these variables (along with control variables). The outcome is work–home distances, calculated as the linear distances between the individuals' places of residence and of work, the censored distances above 200 km are imputed by distances between the geographic centers of the municipalities of residence and of workplace. The dots represent the coefficients of the interaction terms of HOP and month dummies. The bars represent 95%-confidence intervals, based on two-way clustered standard errors by 5-digit occupation and year–month. The omitted reference category is March 2020.
Source: 2% random sample of the Integrated Employment Biographies (IEB) provided by the German Institute for Employment Research (IAB). BERUFENET. Own computations.

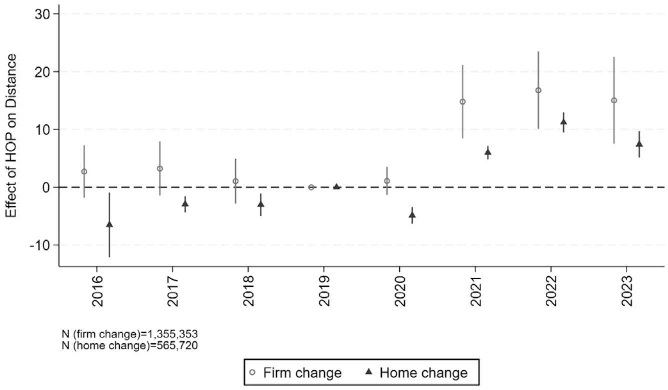


Fig. 3. Work–home distance and HOP among movers.
Notes: The figure reports the results of regression models separately for workers who have either recently moved the firm or the place of living. The outcome is the work–home distance after the move, calculated as the linear distances between the individuals' places of residence and of work, the censored distances above 200 km are imputed by distances between the geographic centers of the municipalities of residence and workplace. We considered employment episodes with a duration of 11 days per month or more. The dots represent the coefficients of the interaction terms of HOP and year dummies. The bars represent 95%-confidence intervals, based on two-way clustered standard errors by 5-digit occupation and year. The omitted reference category is the year 2019.
Source: 2% random sample of the Integrated Employment Biographies (SIAB) provided by the German Institute for Employment Research (IAB). BERUFENET. Own computations.

Fig. 2, we plot the interaction terms of HOP with month dummies. The terms capture the changing effect of the realization of WFH potential on distance relative to March 2020 (the omitted reference category). The figure reveals that the association of HOP with commuting was stable in the four years preceding the Covid-19 pandemic. The coefficients in 2020 do not deviate from this pattern. The early months of the Covid-19 pandemic were marked by uncertainty. It seems that in this environment, people tended to behave conservatively without speculating when the pandemic would end and whether WFH would be retained at the current level. This uncertainty was reduced when several vaccines against the coronavirus was available at the end of 2020. The coefficients in 2021 show that the association of HOP and distance increased significantly relative to other months. This development continued with a slightly lower gradient in 2022 and appears to level off at a new steady state in 2023.[8]

In Table 3, we show the association of pandemic years and HOP on work–home distance from Eq. (5). In columns 1–3, the dependent variable is the work–home distance in kilometers, in columns 4–6, we use the logarithm of the work–home distance. Column 1 is the main specification with all jobs, column 2 covers only new jobs (whose tenure is less than 1 year) and column 3 covers only existing jobs (whose tenure is more than 1 year). In 2020, there was no additional or even a slightly negative additional association of HOP and distance, which mirrors Fig. 2. This has changed in 2021. The coefficient on the 2021 interaction shows the effect is much larger for new jobs, although still significantly positive for existing jobs. These results suggest that the increase in distance is mostly driven by people with high HOP who change jobs or who just start working and are now taking jobs further away than before the pandemic.[9] The significantly positive coefficient for existing jobs is small, but shows that some people with high HOP moved their home to more distant locations while still holding their jobs. These tendencies increased further: Compared to 2021, the coefficient for existing jobs almost doubles in 2022 and almost triples in 2023 . Relocation takes time for deciding, organizing, and implementing. Therefore, the full effect comes with a delay. We confirm this by separating the effects for firm and residence movers. Fig. 3 reports the coefficients of HOP and year interaction terms separately for workers who have either recently moved to a new firm or moved to a new municipality of residence for each year of the entire observation period. Both firm and residence changers clearly increase their distance more if they have jobs with higher WFH potential. At least some people reacted systematically to Covid and the new possibility of WFH by moving out of big cities in the medium run.

The results for the logarithmic work–home distance in columns 4–6 of Table 3 are qualitatively similar but quantitatively around 65 percent smaller when evaluated at the mean compared to the results for the work–home distance in absolute terms. This indicates that long work–home distances, such as when (tele-)commuting between cities of from relatively remote regions, may be an important margin of adjustment.

To illustrate the results quantitatively: Comparing otherwise equal workers with an occupation that has HOP equal to zero vs. one, the commute of the high-HOP workers was on average 17.0 km longer before the pandemic. This is large, given that the median work–home distance in the sample is 7.8 km. Comparing two workers whose occupational HOP differs by one standard deviation (0.23), we expect the work–home distance to differ by about 3.9 km. In 2021, 2022, and 2023, the longer work–home distances associated with a one standard deviation higher HOP were even more pronounced and increased by 0.9 to 2.0 km, corresponding to 23 to 51 percent of the initial difference of

[8] Online Appendix Figure B.2 shows that the same pattern also holds when work–home distance is specified as logarithmic distance.

[9] We cannot rule out that firm changers endogenously move to higher HOP occupations as a response to the pandemic. However, Online Appendix Figure B.3 shows that the distribution of changes in HOP is almost identical for workers who moved between firms in 2019 versus 2022. This suggests that there was no systematic switch towards occupations with higher HOP after the pandemic.

Table 3
Main regression results: Work–home distance.

	All jobs (1)	New jobs (2)	Existing jobs (3)	All jobs (4)	New jobs (5)	Existing jobs (6)
HOP	16.971*	18.589*	16.749*	0.629***	0.654***	0.629***
	(0.030)	(0.042)	(0.030)	(0.000)	(0.001)	(0.000)
HOP × dummy, 1 = 2020	0.621	0.346	0.880*	0.009*	−0.029***	0.017**
	(0.069)	(0.162)	(0.021)	(0.045)	(0.000)	(0.004)
HOP × dummy, 1 = 2021	4.092***	12.300***	2.712***	0.053***	0.125**	0.039***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
HOP × dummy, 1 = 2022	7.071***	17.229***	4.858***	0.094***	0.186***	0.070***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
HOP × dummy, 1 = 2023	8.638***	17.330***	7.067***	0.115***	0.190***	0.097***
	(0.000)	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)
N	66 546 735	13 076 050	53 470 685	66 546 735	13 076 050	53 470 685
R2	0.075	0.070	0.077	0.130	0.117	0.134

Notes: The observation period covers all jobs between 2016–2022, people who worked at least 10 days in a month are included. The outcome for columns (1) to (3) is the work–home distance, calculated as the linear distances between the individuals' places of residence and of work, the censored distances above 200 km are imputed by distances between the geographic centers of the municipalities of residence and of workplace. The outcome for columns (4) to (6) is the natural logarithm of the work–home distance. All regressions include month, 3-digit occupation, 5-digit industry and state fixed effects and age, gender and tenure controls. New jobs have at most 1 year of tenure whereas existing jobs have longer than 1 year of tenure. Two-way clustered standard errors by 5-digit occupation and year in parentheses.

distances. This increase is particularly driven by workers who started their jobs recently (columns 2 and 5). At a one standard deviation higher HOP, workers who started their job in 2021, 2022 or 2023 commuted 2.8 to 4.0 km further, which corresponds to 73 and 100 percent of the baseline difference of job starters before the pandemic.

Robustness. In our main specification, we measure the WFH potential as a continuous variable. This corresponds to a difference-in-differences model with continuous treatment as discussed by Callaway et al. (2024). As an alternative, we divide the distribution of HOP in 2019 into four quartiles and interact three of the resulting quartile-dummies with year-dummies. As Fig. 4 reveals, the main results are mostly driven by the fourth quartile. Comparing workers with occupations at the two lowest quartiles does not yield any statistically or economically significant differences in work–home distances. But jobs in the top quartile are related to around 5 more kilometers of work–home distance compared to jobs in the bottom quartile. For the third quartile, the pattern is similar but much smaller. Furthermore, while a certain effect in the pandemic year 2021 is visible for all quartiles, the only continued increase appears at the top. In Fig. 5, we repeat the main monthly specification but use a dummy variable indicating the top quartile instead of a continuous variable. The results are very similar to the baseline both regarding the pattern of an increasing effect and the magnitudes. Alternatively, using a variable indicating a HOP above the median yields the same pattern but coefficients that are about half the size. Since choosing a cutoff is arbitrary, we prefer to use the continuous HOP variable for the upcoming analyses.

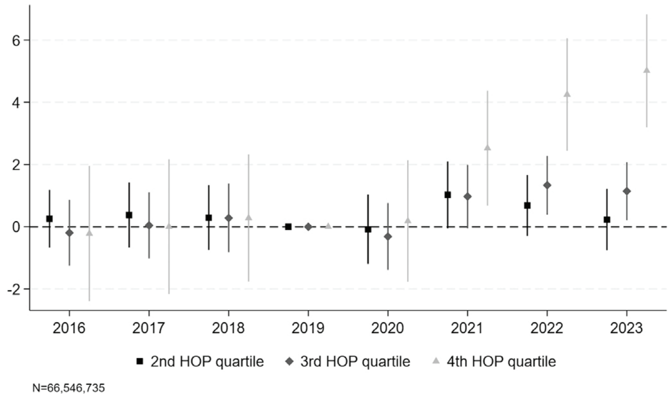


Fig. 4. Realization of WFH potential on work–home distance — by HOP-quartiles.
Notes: The figure reports the results of a regression model with the effects of the three upper HOP quartiles on individual commuting behavior for workers; reference group is the 1st HOP quartile. The outcome is the work–home distance, calculated as the linear distances between the individual's places of residence and of work, the censored distances above 200 km are imputed by distances between the geographic centers of the municipalities of residence and workplace. We considered employment episodes with a duration of 11 days per month or more. The dots represent the coefficients of the interaction terms of HOP and year dummies. The bars represent 95%-confidence intervals, based on two-way clustered standard errors by 5-digit occupation and year. The omitted reference category is the year 2019.
Source: 2% random sample of the Integrated Employment Biographies (SIAB) provided by the German Institute for Employment Research (IAB). BERUFENET. Own computations.

5.2. How the relocation of workplaces or residences contributes to increasing distances

To further disentangle the different margins along which workers can adjust to the increased acceptance of WFH, we decompose the overall increase of the average work–home distance between 2019 and 2023 into the contributions of various groups that differ in terms of residential or job mobility. Table 4 reports the results of this exercise. Each row represents a group of workers, defined by their residential and/or job mobility between June 2019 and June 2023. In the last two columns, we report the group's share in total employment in June 2023 and the contribution of each group to the overall distance change of 2.98 km. 36% of workers have changed neither jobs nor home and, hence, have zero change in their distance. 12% work at the same firm but have moved to a different home and thereby have increased their distance by an average of 3.15 km. Among those who switch to new jobs, we observe a clear pattern of larger distance increases for jobs with higher HOP. The group that increased the distance the most (around 10 km) are workers who switched to jobs with higher HOP while either remaining in their previous home or moving to a new one. Together they constitute 7% of the work force but contribute 24% of the overall change of the average distance. People who switched to jobs with the same HOP also increased their distance, especially if they also changed homes (5.34 km). Distance changes among people who switched to jobs with smaller HOP are also positive but smaller in magnitude. Taken together, all workers who were employed in both years have increased their average distance by 2.46 km, which

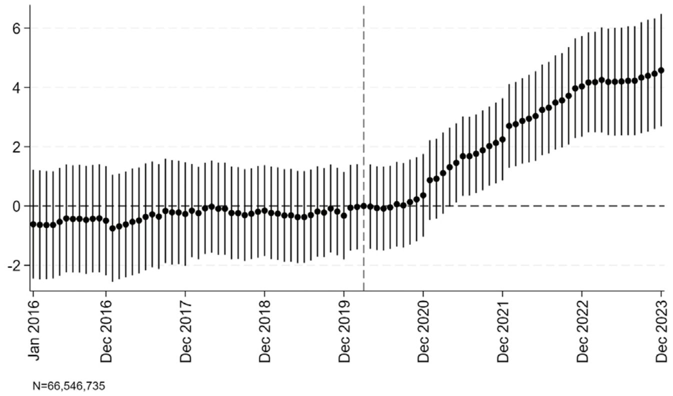


Fig. 5. Effect of the realization of WFH potential on work–home distance — top-quartile HOP.
Notes: The figure reports the results of a regression model of individual work–home distances on an indicator variable for a HOP above the top quartile of the distribution in 2019, year–month-dummies and interactions of these variables (along with control variables). The outcome is the work–home distance, calculated as the linear distances between the individuals' places of residence and of work, the censored distances above 200 km are imputed by distances between the geographic centers of the municipalities of residence and of workplace. The dots represent the coefficients of the interaction terms of HOP and month dummies. The bars represent 95%-confidence intervals, based on two-way clustered standard errors by 5-digit occupation and year–month. The omitted reference category is March 2020.
Source: 2% random sample of the Integrated Employment Biographies (IEB) provided by the German Institute for Employment Research (IAB). BERUFENET. Own computations.

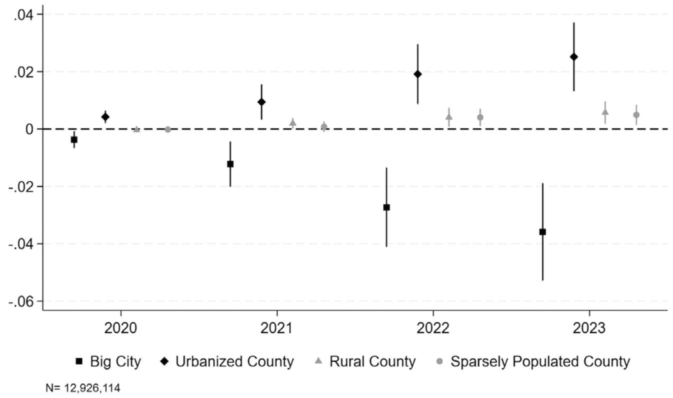


Fig. 6. HOP and residential location of individuals who worked and lived in big cities in 2019.
Notes: The figure reports the results of a series of four separate linear probability regression models for workers who worked and lived in big cities in 2019. The outcomes are dummy variables that indicate in which of the four county categories the worker lives. We considered employment episodes with a duration of 11 days per month or more. The dots represent the coefficients of the interaction terms of HOP and year dummies. The bars represent 95%-confidence intervals, based on two-way clustered standard errors by 5-digit occupation and year. The omitted reference category is the year 2019.
Source: 2% random sample of the Integrated Employment Biographies (SIAB) provided by the German Institute for Employment Research (IAB). BERUFENET. Own computations.

contributes by 64% of the overall increase. 23% of workers observed in 2023 have not been employed in 2019. Their average work–home distance is 4.70 km longer than the distance of those who left the workforce before 2023, which results in a 36% contribution to the total increase. To sum up, among continuously employed, the largest contributions to the increase of the average work–home distance are mainly driven by three types of mobility. First, workers who moved to a different home and hold the same job (12%). Second, workers who switched to jobs with the same HOP, while living in the same home (18%). Finally, workers who switched to jobs with higher HOP (regardless of home change) contribute to the overall distance increase by 24% (17% plus 7%).

5.3. *The geography of telecommuting: Big cities, donuts, and rural areas*

Next, we explore how working from home affects the economic geography of the German labor market. We do this firstly by adding a big city dummy to the baseline regression, secondly by analyzing where people who live 2019 in big cities will live in the following years, thirdly by analyzing whether workers are more likely to work in urban or rural areas over time — separately for different types of counties in which they live.

In Table 5, we focus on workers who have recently started a new job and add a variable that indicates if the place of work is a big city (100,000 inhabitants or more), along with interactions of HOP and the (post-)pandemic years. Column 1 repeats the result of column 5 from Table 3. Column 2 reveals that people commuting to bigger cities have longer work–home distances. Interestingly, column 3 shows that this pattern is more pronounced for workers who started their new jobs during the pandemic. In column 4 our model is complemented with the interaction of HOP and working in big cities as well as triple-interaction terms. Before 2020, workers in high-HOP occupations in big cities had lower work–home distances. This reflects the observation by Althoff et al. (2022) that jobs with high remote work potential have always been concentrated in big cities and people holding those jobs appear to

Table 4
Decomposition of the average change in work-home distances 2019–2023.

Change				Share in	Contribution to
Job	HOP	Home	Distance	2023	overall change
No		No	0	0.36	0%
No		Yes	3.15	0.12	12%
Yes	Same	No	3.94	0.14	18%
Yes	Same	Yes	5.34	0.04	7%
Yes	Smaller	No	1.35	0.03	2%
Yes	Smaller	Yes	1.10	0.01	0%
Yes	Bigger	No	10.39	0.05	17%
Yes	Bigger	Yes	10.80	0.02	7%
Average of stayers			2.46	0.77	64%
	Entry Exit		4.70	0.230	36%
Average of all			2.98		

Note: We use the month of June as a benchmark and focus on job and home changes between year 2019 and 2023. Labor force grows by around 1% during this time. When calculating the contribution of each category to the overall distance increase, we use 2023 shares as benchmark. We consider a person having a job with the "same" HOP, if the HOP change between two years is less than 0.1 in absolute value (half of a standard deviation). If the HOP change is smaller than −0.1, the person is considered switching to a job with "smaller" HOP, and if the HOP change is larger than 0.1, the person is considered switching to a job with "bigger" HOP. A person is considered to change "home" if the person moves to a different municipality or work–home distance changes even if the person works at the same firm and resides in the same municipality (move within city borders). The contribution is calculated by multiplying the distance change with the share of the group (4th and 5th column) and dividing by the total distance change. The distances are calculated as the linear distances between the individual's place of residence and workplace, the censored distances above 200 km are imputed by distances between the geographic centers of the municipalities of residence and of workplace.

have had either a preference for living in those bigger cities or against commuting and were better able to afford the cost of living in those cities. The coefficient of the triple interaction for later years indicates that this tendency was increasingly reversed in 2021, 2022, and 2023. In other words: people who work in big cities live increasingly further away from their employers, especially when they are able to commute virtually rather than physically.

Table 5
Regression results: Work–home distance in big cities.

	(1)	(2)	(3)	(4)
HOP	0.654*** (0.001)	0.646*** (0.001)	0.656*** (0.001)	0.794*** (0.000)
HOP × dummy, 1 = 2020	−0.029*** (0.000)	−0.029*** (0.000)	−0.038*** (0.000)	−0.048*** (0.001)
HOP × dummy, 1 = 2021	0.125** (0.001)	0.125** (0.001)	0.110** (0.001)	0.066* (0.012)
HOP × dummy, 1 = 2022	0.186*** (0.001)	0.186*** (0.001)	0.156*** (0.001)	0.102** (0.004)
HOP × dummy, 1 = 2023	0.190*** (0.001)	0.189*** (0.001)	0.159** (0.002)	0.077* (0.021)
dummy, 1 = Big city		0.061** (0.003)	0.035* (0.044)	0.159*** (0.000)
dummy, 1 = Big city × dummy, 1 = 2020			0.022*** (0.000)	0.014* (0.045)
dummy, 1 = Big city × dummy, 1 = 2021			0.038*** (0.000)	0.004 (0.631)
dummy, 1 = Big city × dummy, 1 = 2022			0.073*** (0.000)	0.032* (0.029)
dummy, 1 = Big city × dummy, 1 = 2023			0.076*** (0.000)	0.010 (0.447)
HOP × dummy, 1 = Big city				−0.336** (0.005)
HOP × dummy, 1 = Big city × dummy, 1 = 2020				0.026* (0.043)
HOP × dummy, 1 = Big city × dummy, 1 = 2021				0.097** (0.002)
HOP × dummy, 1 = Big city × dummy, 1 = 2022				0.119** (0.003)
HOP × dummy, 1 = Big city × dummy, 1 = 2023				0.182** (0.001)
N	13 076 050	13 076 050	13 076 050	13 076 050
R2	0.117	0.118	0.118	0.118

Notes: Regression period covers all new jobs (at most 1 year of tenure) between 2016–2022, people who worked at least 10 days in a month are included. The outcome is the natural logarithm of the work–home distance, calculated as the linear distances between the individual's place of residence and workplace, the censored distances above 200 km are imputed by distances between the geographic centers of the municipalities of residence and of workplace. All regressions include month, 3-digit occupation, 5-digit industry and state fixed effects and age, gender and tenure controls. Two-way clustered standard errors by 5-digit occupation and year in parentheses.

Next, we delve more into the geography of working from home by examining whether the relationship between HOP and the choice of residence changes over time. We distinguish between big cities with more than 100,000 inhabitants, urbanized counties that mostly directly surround big cities, rural counties, and sparely populated rural counties (classification of the BBSR).

In Fig. 6 we focus on individuals who worked and lived in a big city in 2019. We show the results of four separate regression models similar to those in Table 3, but with four different dependent dummy variables indicating in which of the four county types an individual lives. The coefficients reflect how the probability of living in the various county types changed for workers in a high HOP job since 2019. Workers who lived and worked in 2019 in big cities became less likely to live in big cities if their jobs that have a high HOP, and became more likely to live in urbanized counties. Mobility to (very) rural counties plays a minor role. This suggests that very few workers in high-HOP occupations have the possibility to fully disentangle their places of work and residence. More likely, they still commute to their workplace for a certain fraction of their working days and hence, they still need to reside in the vicinity of their workplaces, albeit at a larger distance than before WFH became acceptable. This contributes to a "donut effect" as described by Ramani et al. (2024).

Finally, we stay within this framework to study the relationship between HOP and the place of work separately for residents of each of the four county types in 2019. Fig. 7 summarizes the main coefficients of four sets of regressions: Each panel represents a residence type in 2019. The markers within a panel represent the coefficients of the four regressions, where the dependent dummy variable indicates the county type of the workplace. The top left panel shows that workers who lived in a big city in 2019 become even more likely to work where they live if they have high-HOP occupations and they become less likely to work in a surrounding urbanized county. The same pattern applies to residents of urbanized and rural counties, who are also more likely to work for firms in a big city the higher their occupation's HOP and less likely to work in the suburbs or more remote places. This tendency is much smaller among residents of the most rural counties, arguably because the big cities lie outside of many workers' reservation radius even under hybrid WFH arrangements.

The labor markets of big cities offer a large number of skilled workers (Behrens et al., 2014). The possibility of WFH could also give companies in rural areas access to urban labor markets — by offering

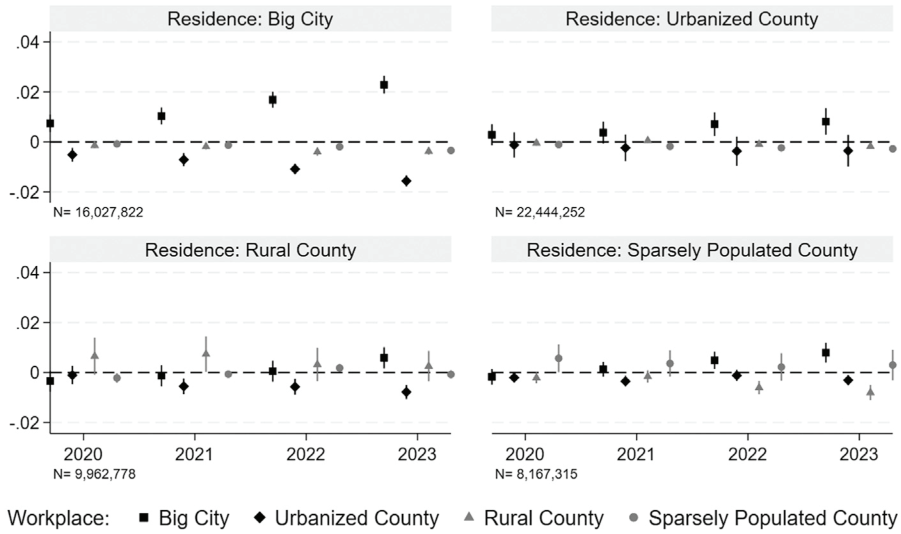


Fig. 7. HOP and workplace location by residence in 2019.
Notes: The figure reports the results of a series of four separate linear probability regression models for workers who lived in the same county category in 2019. The outcomes are dummy variables that indicate in which of the four county categories the worker works in later years. We considered employment episodes with a duration of 11 days per month or more. The dots represent the coefficients of the interaction terms of HOP and year dummies. The bars represent 95%-confidence intervals, based on two-way clustered standard errors by 5-digit occupation and year. The omitted reference category is the year 2019.
Source: 2% random sample of the Integrated Employment Biographies (SIAB) provided by the German Institute for Employment Research (IAB). BERUFENET. Own computations.

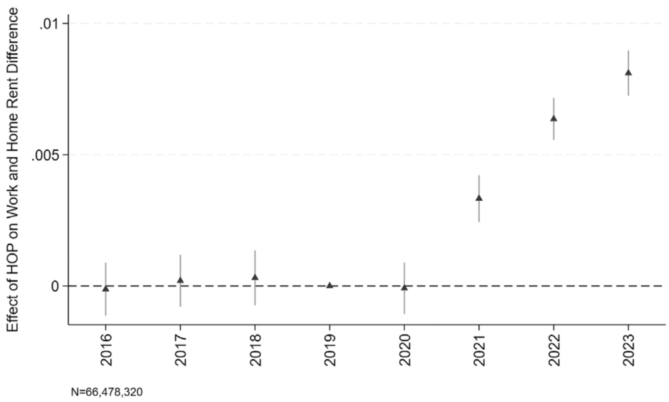


Fig. 8. HOP and rent difference between the workplace and place of residence.
Notes: The figure reports the results of a regression of the difference between rents at the workplace versus residence counties on HOP, year–month-dummies and interactions of these variables (along with control variables). The outcome is the difference between the natural logarithms of the median rents per square meter in the counties of the individuals' workplace and of their place of residence at fixed 2018 prices. The dots represent the coefficients of the interaction terms of HOP and year dummies. The bars represent 95%-confidence intervals, based on two-way clustered standard errors by 5-digit occupation and year. The omitted reference category is 2019.
Source: 2% random sample of the Integrated Employment Biographies (IEB) provided by the German Institute for Employment Research (IAB). BERUFENET. Rent prices at the county level were provided by Mense et al. (2023). Own computations.

WFH jobs to qualified city dwellers who do not want to move away from their city. However, the top panels of Fig. 7 do not provide evidence that this is systematically the case: there are no positive coefficients for workplaces in rural or very rural counties.

5.4. Rent analysis

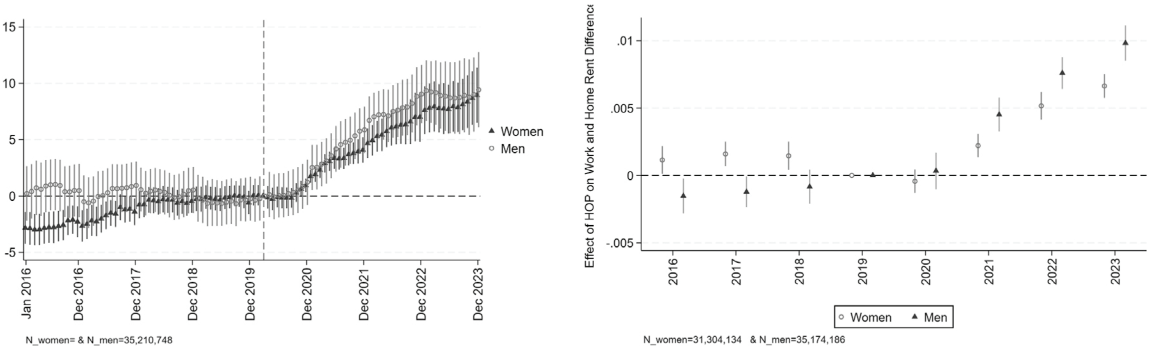
From the workers' perspective, big cities offer good job opportunities. However, big cities are also more expensive, mainly due to higher rent prices. This can be a reason for workers to live in other areas if WFH allows them to work in more expensive regions as well. We examine this consideration by regressing the (natural logarithm) of the median rent of the workplace and residence county on the same explanatory variables as in Table 6. We focus on workers who recently started their job.

Variation of rents could come from two sources: Geographical variation of where people work and live and variation of rents over time within a county. To eliminate the latter source of variation, we fix the rent prices at the 2018 level in subsequent analyses.

The rent level of the workplace county is the dependent variable in column 1 of Table 6, that of the residence county in 2, and the difference in 3. The positive coefficients of HOP in columns 1 and 2 confirm that high-HOP jobs as well as the residences of the people holding those jobs were concentrated in more expensive housing markets, that is, in big cities and their surroundings. The interaction of the years with HOP is positive from 2022 on in column 1, but negative in column 2. In other words: The rent prices at the residence of people in high HOP jobs decrease, the rent prices at the firms location increase. Jobs were located in more expensive regions than before, but workers chose cheaper regions to live. Thus, the work–home rent difference increased. Indeed, plotting the coefficients for rent differences in Fig. 8 confirms that the difference at fixed prices was flat until 2020. Afterwards, we see a striking increase from 2021 on.

5.5. Gender differences

Commuting has a profound gender dimension. Women work on average much closer to where they live and have a higher willingness to pay for a shorter commute, which means that they require a higher wage in order to commute further (Le Barbanchon et al., 2020). Since this restricts the number of potential employers women have access to, the gender commuting gap contributes significantly to the gender pay gap. Liu and Su (2022) point out that this gap is smaller for individuals living near big city centers where high-wage jobs are concentrated. The increased acceptance of WFH might level the playing field as it provides access to those jobs also away from big city centers without the necessity to commute longer distances. This is also in line with Nagler et al.



(a) Work-home distance.

(b) Work-home rent difference.

Fig. 9. HOP and work-home distance and rent difference.
Notes: The figure reports the results of a regression of individual work-home distances (Panel a) and the difference between rents at the workplace and at the residence counties (Panel b) on HOP, year-month-dummies and interactions of these variables (along with control variables). Work-home distances are calculated as the linear distances between the individual's place of residence and workplace, whereas the censored distances above 200 km are imputed by distances between the geographic centers of the municipalities of residence and of workplace (Panel a). The difference between rents at the workplace and at the residence county is calculated as natural logarithm of the difference of median rents per square meter for the county of the individuals' workplace and place of residence at 2018 fixed prices (Panel b). The dots represent the coefficients of the interaction terms of HOP and year (Panel a) or month (Panel b) dummies. The bars represent 95%-confidence intervals, based on two-way clustered standard errors by 5-digit occupation and year. The omitted reference category is March 2020.
Source: Source: 2% random sample of the Integrated Employment Biographies (IEB) provided by the German Institute for Employment Research (IAB). BERUFENET. Rent prices at the county level are provided by Mense et al. (2023). Own computations.

Table 6
Regression results: Work-home rent difference.

	Workplace (1)	Residence (2)	Diff (3)
HOP	0.056*** (0.000)	0.055*** (0.000)	0.001 (0.857)
HOP × dummy, 1 = 2020	0.001 (0.616)	0.001 (0.544)	−0.000 (0.843)
HOP × dummy, 1 = 2021	0.001 (0.291)	−0.002* (0.043)	0.003*** (0.000)
HOP × dummy, 1 = 2022	0.002* (0.036)	−0.004** (0.002)	0.006*** (0.000)
HOP × dummy, 1 = 2023	0.002* (0.043)	−0.006*** (0.000)	0.008*** (0.000)
N	66 478 320	66 478 320	66 478 320
R2	0.571	0.493	0.048

Notes: Regression period covers all jobs 2016–2023, people who worked at least 10 days in a month are included. The outcomes are the natural logarithms of the median rent per square meter of the workplace county for column (1) and of the residence county for column (2). The outcome for column (3) is the difference of the outcomes for columns (1) and (2). All regressions include month, 3-digit occupation, 5-digit industry and state fixed effects and age, gender and tenure controls. Regression includes interaction term for all years (the omitted reference category is 2019), but we only report the coefficients of 2020 after as we do not observe pre-trend. Two-way clustered standard errors by 5-digit occupation and year in parentheses.

(2024), who find that WFH reduces the gender gap in the willingness to pay for a shorter commute. This suggests that women and men are more likely to accept jobs at similar distances if they offer the possibility of WFH.

In panel a of Fig. 9, we report the results of our main analyses separately for women and men. The effects of the realization of WFH on work–home distances are moderately but not significantly larger for men in 2022 than for women, but this is equalized in 2023. By contrast, the panel b of Fig. 9 indicates that the effect of HOP on fixed 2018 rent differences between county of work and county of residence is more pronounced for men in 2022 and 2023. This suggests that it is men who benefit most from the possibility to work from home and reach employers in more remote high-rent regions from their comparatively lower rent residences.

6. Conclusion

In this study, we investigate changes in work–home distance following the Covid-19 pandemic, which introduced increased possibilities for WFH. Leveraging unique administrative data from Germany, we analyze employment records, detailed occupation categories, the WFH potential based on working conditions, and work/residence locations. Our findings reveal a significant increase in work–home distance since 2021 for individuals with higher WFH potential, indicating a departure from the stable patterns observed before the pandemic.

While this effect is more pronounced for new jobs, there is still a smaller yet statistically significant impact on existing jobs. These results indicate that individuals starting new jobs are accepting positions located farther away compared to pre-pandemic circumstances, and some individuals who retained their jobs have also chosen to relocate their place of residence to more distant places.

Our findings demonstrate that the increased practice of WFH has induced behavioral changes in the labor market, influencing job search strategies and relocation decisions. As a consequence, local labor markets have expanded in terms of geographic scale. This has implications for individuals who can reach better fitting jobs even if they are located farther away and for firms who increase their catchment areas and are able to draw from a larger pool of applicants. The resulting increase of matching efficiency even has the potential to increase aggregate productivity and incomes.

These evolving patterns have profound implications for the future of labor markets, fostering new opportunities for both firms and workers and facilitating enhanced integration of local labor markets on both national and global scales.

Departing from this basis, there are considerable opportunities for future research. Key questions concern the way how labor market outcomes are shaped in a world of new locality conditions. Does the matching improve in view of increased relevant pools of jobs and workers? I.e., is mismatch reduced and can search times be shortened, as already simulated in Wolter et al. (2021)? How do wages adjust, and which role do improved matching and the amenity value of WFH play (Aksoy et al., 2023)? How are potential gains divided between the labor market sides? Are the new options a chance for women to improve their labor market outcomes? We expect an evolving literature to address these issues from different angles, and will actively contribute to that.

CRediT authorship contribution statement

Sena Coskun: Writing – review & editing, Writing – original draft, Visualization, Validation, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Wolfgang Dauth:** Writing – review & editing, Writing – original draft, Validation, Supervision, Project administration, Methodology, Investigation, Conceptualization. **Hermann Gartner:** Writing – review & editing, Writing – original draft, Visualization, Investigation, Formal analysis. **Michael Stops:** Writing – review & editing, Writing – original draft, Methodology, Data curation, Investigation. **Enzo Weber:** Writing – review & editing, Writing – original draft, Supervision, Methodology, Investigation, Conceptualization.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.jue.2026.103832.

References

Akan, M., Barrero, J.M., Bloom, N., Bowen, T., Buckman, S.R., Davis, S.J., Kim, H., 2025. The New Geography of Labor Markets. NBER Working Paper 33582.
Aksoy, C.G., Barrero, J.M., Bloom, N., Davis, S.J., Dolls, M., Zarate, P., 2023. Time savings when working from home. AEA Pap. Proc. 113, 597–603.
Alipour, J.-V., Fadinger, H., Schymik, J., 2021. My home is my castle – The benefits of working from home during a pandemic crisis. J. Public Econ. 196.
Alipour, J.-V., Falck, O., Schüller, S., 2023. Germany's capacity to work from home. Eur. Econ. Rev. 151, 104354.
Althoff, L., Eckert, F., Ganapati, S., Walsh, C., 2022. The geography of remote work. Reg. Sci. Urban Econ. 93 (103770).
Arntz, M., Yahmed, S.B., Berlingieri, F., 2020. Working from home and COVID-19: The chances and risks for gender gaps. Intereconomics 55 (6), 381–386.
Atkin, D., Schoar, A., Shinde, S., 2023. Working from Home, Worker Sorting and Development. NBER Working Paper 31515.
Barrero, J.M., Bloom, N., Davis, S.J., 2023. The evolution of work from home. J. Econ. Perspect. 37 (4), 23–50.
Behrens, K., Duranton, G., Robert-Nicoud, F., 2014. Productive cities: Sorting, selection, and agglomeration. J. Political Econ. 122 (3), 507–553.
Van den Berg, G.J., Gorter, C., 1997. Job search and commuting time. J. Bus. Econom. Statist. 15 (2), 269–281.
Bick, A., Blandin, A., Mertens, K., 2023. Work from home before and after the COVID-19 outbreak. Am. Econ. J.: Macroecon. 15 (4), 1–39.
Bloom, N., Davis, S.J., Zhestkova, Y., 2021. COVID-19 shifted patent applications toward technologies that support working from home. AEA Pap. Proc. 111, 263–266.
Boll, C., Müller, D., Osiander, C., Schüller, S., 2024. Working from home and parental childcare division: Evidence from two years of the COVID-19 pandemic. Soc. Politics: Int. Stud. Gend. State Soc. jxae031.
Brueckner, J.K., Kahn, M.E., Lin, G.C., 2023. A new spatial hedonic equilibrium in the emerging work-from-home economy? Am. Econ. J.: Appl. Econ. 15 (2), 285–319.
Bruns, F., Matthes, B., Stops, M., 2025. HOP – an occupational indicator for the potential of working from home. J. Econ. Stat. Ahead-of-Publication.
Callaway, B., Goodman-Bacon, A., Sant'Anna, P.H.C., 2024. Difference-in-Differences with a Continuous Treatment. NBER Working Paper 32117.
Card, D., 1992. Using regional variation in wages to measure the effects of the federal minimum wage. ILR Rev. 46 (1), 22–37.
Correia, S., 2016. Linear Models with High-Dimensional Fixed Effects: An Efficient and Feasible Estimator. Working Paper, Duke University, URL: https://scorreia.com/research/hdfe.pdf.
Coskun, S., Dauth, W., Gartner, H., Stops, M., Weber, E., 2026. Working from Home Increases Work-Home Distances: Replication Archive. Mendeley Data, V1, http://dx.doi.org/10.17632/7g7cz8w7pt.1.
Dauth, W., Findeisen, S., Moretti, E., Suedekum, J., 2022. Matching in cities. J. Eur. Econ. Assoc. 20 (4), 1478–1521.
Dauth, W., Haller, P., 2020. Is there loss aversion in the trade-off between wages and commuting distances? Reg. Sci. Urban Econ. 83, 103527.
Dingel, J.I., Neiman, B., 2020. How many jobs can be done at home? J. Public Econ. 189, 104235.
Fujita, M., Ogawa, H., 1982. Multiple equilibria and structural transition of non-monocentric urban configurations. Reg. Sci. Urban Econ. 12 (2), 161–196.
Ilham, M.A., Fonzone, A., Fountas, G., Mora, L., 2024. To move or not to move: A review of residential relocation trends after COVID-19. Cities 151, 105078.
Kagerl, C., Starzetz, J., 2023. Working from home for good? Lessons learned from the COVID-19 pandemic and what this means for the future of work. J. Bus. Econ. 93, 229–265.
Le Barbanchon, T., Rathelot, R., Roulet, A., 2020. Gender differences in job search: Trading off commute against wage. Q. J. Econ. 136 (1), 381–426.
Lei, C., 2024. Revisit Labor Market Concentration Under Work-From-Home: An Integration of Labor Market Boundaries. Working Paper, University of Maryland, http://dx.doi.org/10.2139/ssrn.5030418.
Liu, S., Su, Y., 2022. The geography of jobs and the gender wage gap. Rev. Econ. Stat. 136 (1), 1–27.
Liu, S., Su, Y., 2024. The Effect of Working from Home on the Agglomeration Economies of Cities: Evidence from Advertised Wages. SSRN.
Mense, A., Michelsen, C., Kholodilin, K.A., 2023. Rent control, market segmentation, and misallocation: Causal evidence from a large-scale policy intervention. J. Urban Econ. 134, 103513.
Monte, F., Porcher, C., Rossi-Hansberg, E., 2023. Remote Work and City Structure. NBER Working Paper 31494.
Nagler, M., Rincke, J., Winkler, E., 2024. Working from home, commuting and gender. J. Popul. Econ. 37 (58).
Ramani, A., Alcedo, J., Bloom, N., 2024. How working from home reshapes cities. Proc. Natl. Acad. Sci. 121 (45), e2408930121.
Schmucker, A., Seth, S., Vom Berge, P., 2023. Sample of Integrated Labour Market Biographies (SIAB) 1975–2021. FDZ-Datenreport 02/2023.
Wolter, M.I., Mönnig, A., Maier, T., Schneemann, C., Steeg, S., Weber, E., Zika, G., 2021. Langfristige Folgen der Covid-19-Pandemie für Wirtschaft, Branchen und Berufe. IAB-Forschungsbericht 02/2021.