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DISCUSSION PAPER SERIES

IZA DP No. 16855

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# ABSTRACT

## Working from Home Increases Work-Home Distances

This paper examines how the shift towards working from home during and after the Covid-19 pandemic shapes the way how labor market and locality choices interact. For our analysis, 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 Covid-19 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.

**JEL Classification:** J61, R23

**Keywords:** working from home, commuting, urban labor markets

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# 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). For the labor market, 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 acceptability of working from home (WFH) in the wake of the Covid-19 pandemic has affected commuting behavior. The pandemic has shifted the standards how work is organized, and especially where it is carried out (Aksoy et al., 2022). Contact restrictions fostered working from home, investment into the digital infrastructure of the firms, new standards for operational processes, as well as communication and relevant technological innovations (Bloom et al., 2021).

Arguably, WFH will not remain on lockdown levels after the pandemic. However, several factors make it likely that a certain shift is persistent. First, the shock was collective, lending itself to changing the standard. Second, considerable investments were made. Third, in many countries, competition for labor intensified markedly over time and especially after the pandemic. WFH becomes a widespread requirement from the workers' side. Indeed, empirical evidence shows that levels remain greatly elevated. 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.

Local proximity has always been a key factor in determining in which places people take up work, or conversely, where they settle. With the Covid shock on the intensity of WFH, the requirement of proximity has become less strict. Thus, the shock may have led to a paradigm change for the way how the labor market and locality choices interact. On the one hand, employment opportunities determine settling decisions and shape patterns across rural and urban areas. On the other hand, regional boundaries and frictions to mobility are important parameters for the functioning of the labor market. Its capacity of matching jobs to people is determined by the relevant regional radius both for firms and individuals. Availability of WFH might have changed the search behavior of both of them.

Commuting is costly both in terms of monetary expenses and the opportunity cost of the time spent commuting. In absence of WFH, this implies that there is a cost increasing in the distance between the place of residence and the workplace, which must be compensated either by a higher wage or lower housing costs (Dauth and Haller, 2020). The possibility to telecommute reduces the number of trips and therefore the costs associated with each kilometer between residence and workplace. Other things equal, we therefore expect to see increases in this distance after working from home has become more widely accepted.

We study if and how German employees have reacted to the increased acceptability 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? Do we observe changes along 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, Figure 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 particularly likely to work from home for at least a fraction of their workweek. Other occupations, by contrast, require physical contact and therefore require workers must continue commuting to work every day. In this paper, we exploit the heterogeneity of how well occupations are suited for remote work to identify the effect of WFH on work-home distances.

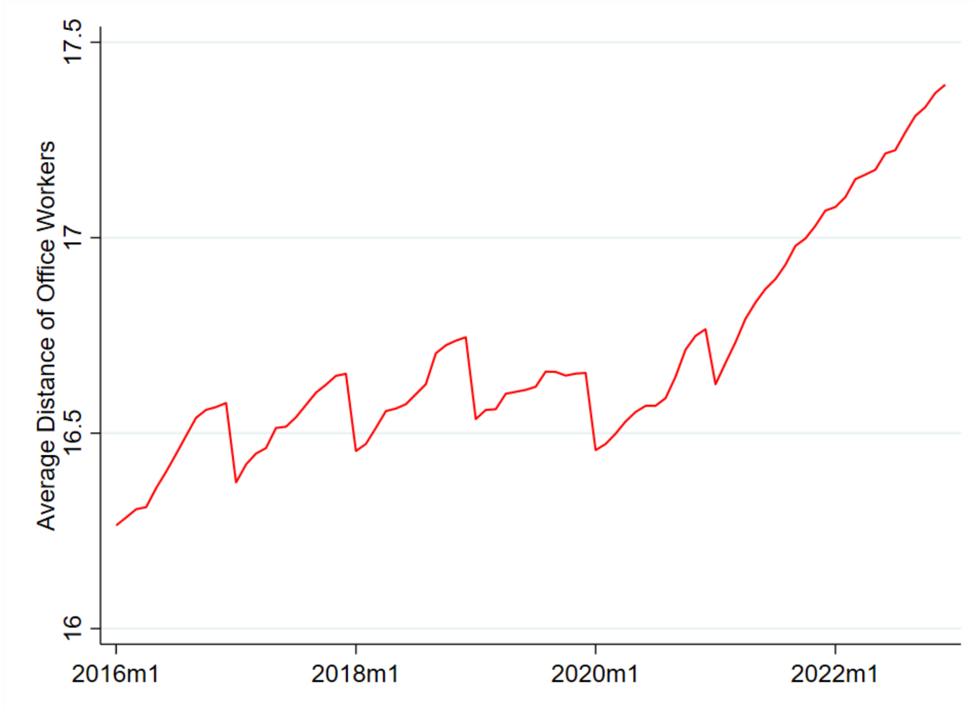



Figure 1: Evlolution of work-home distances for office workers

*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 driving distances between geographic centers of the municipality of the individual's place of residence and workplace and are winsorized at 200km.*
*Source: 2 % random sample of the Integrated Employment Biographies (IEB) provided by the German Institute for Employment Research (IAB). BERUFENET. Own computations.*

We deal with the corona shock as a natural experiment. Thereby, we make use of the fact that the shock hit occupations differently according to their WFH potential. This potential is defined as the possibility to conduct the relevant tasks remotely. For this purpose, we utilize a new measure for WFH potential (Home Office Potential Indicator or short HOP Indicator) for the German labor market based on the German expert data base BERUFENET. Similar to its US equivalent O*Net, this data base represents a rich source of occupational information and comprises, amongst others, a broad set of working conditions.

We combine the data on WFH potential with large administrative data on employment biographies in Germany. This provides the opportunity to analyze a broad set of outcomes such as 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. In contrast, the first pandemic year 2020 did not show any changes. The effect 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. For existing jobs we find a clearly smaller but still significant positive effect on work-home distance. Apparently, at least some people with high WFH potential have relocated their residences to places further away. While people living and working in big cities have typically shorter commuting distances, this tendency was reduced since 2021. People work in big cities live increasingly further away from their employers, especially when they are able to commute virtually rather than physically. This implies that the relevant labor markets of big cities have expanded. In the same vein, while new jobs and the people holding them are more likely to be located in more expensive housing markets, this tendency weakens since 2021. This suggests that WFH is pervasive and offers opportunities also to firms away from urban centers to attract skilled employees. 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 real estate prices at the workplace and the place of residence has increased more strongly for men.

The paper is structured as follows. Section 2 introduces the administrative labor market data as well as the BERUFENET data base and the construction of the HOP indicator. Section 3 discusses our research design, and section 4 presents the estimation results. The last section concludes.

## 2 Data

### 2.1 Employment, commuting, and rent prices

We use a 2 percent random sample of the Integrated Employment Biographies (IEB v17.00.00-202212) 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 set follows the individuals during periods of employment and unemployment on a daily base and provides

[1] This data set is very similar to the publicly available SIAB but contains more recent data up to 2022, while SIAB is only updated bi-annually and only covers data up to 2021 (for more details see Schmucker et al. (2023)).

information on education, occupations, wages and others.[2]

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. We proxy the commuting distance by the distance between the center of the workplace municipality and the center of the municipality of residence. This means that our measure of commuting distance is driven by commutes across municipality borders.[3] Distances are car driving distances between the municipality centers (see Huber and Rust, 2016, for the calculation of driving distances using OpenStreetMap data). Commuting distances within cities are set to zero (and 1 km for logarithmic distances).

Figure 2 shows the evolution of average commuting distances of all workers and by gender. There is a secular increase of distances in total and for both male and female workers. This may be caused by improvements in the transportation infrastructure or disproportionably increasing housing prices in the city centers, driving mid-class households to the urban fringe. The substantial gender difference is a well-known fact and reflects that indifference curves between wage and commute are steeper for women, meaning that they need a higher wage to compensate them for a certain commuting distance (Le Barbanchon et al., 2020).

[2]See appendix Section A for more details on data preparation.

[3]We will refine this during the course of this project. We expect that the exact geocodes of workplace and residence locations will be available by mid-2024, which we will use to calculate exact distances.

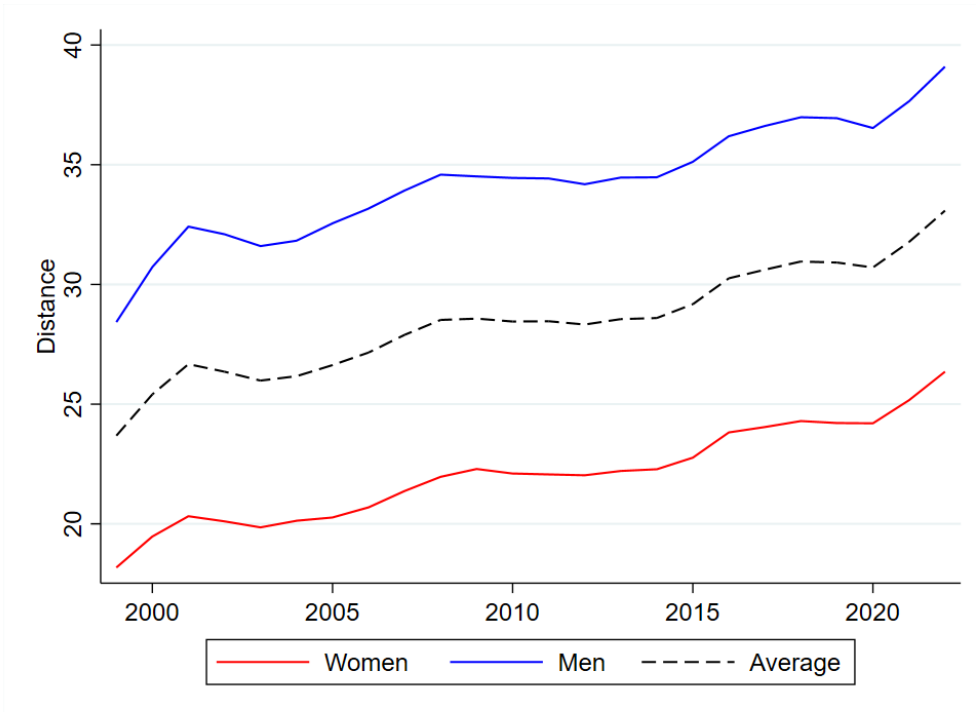
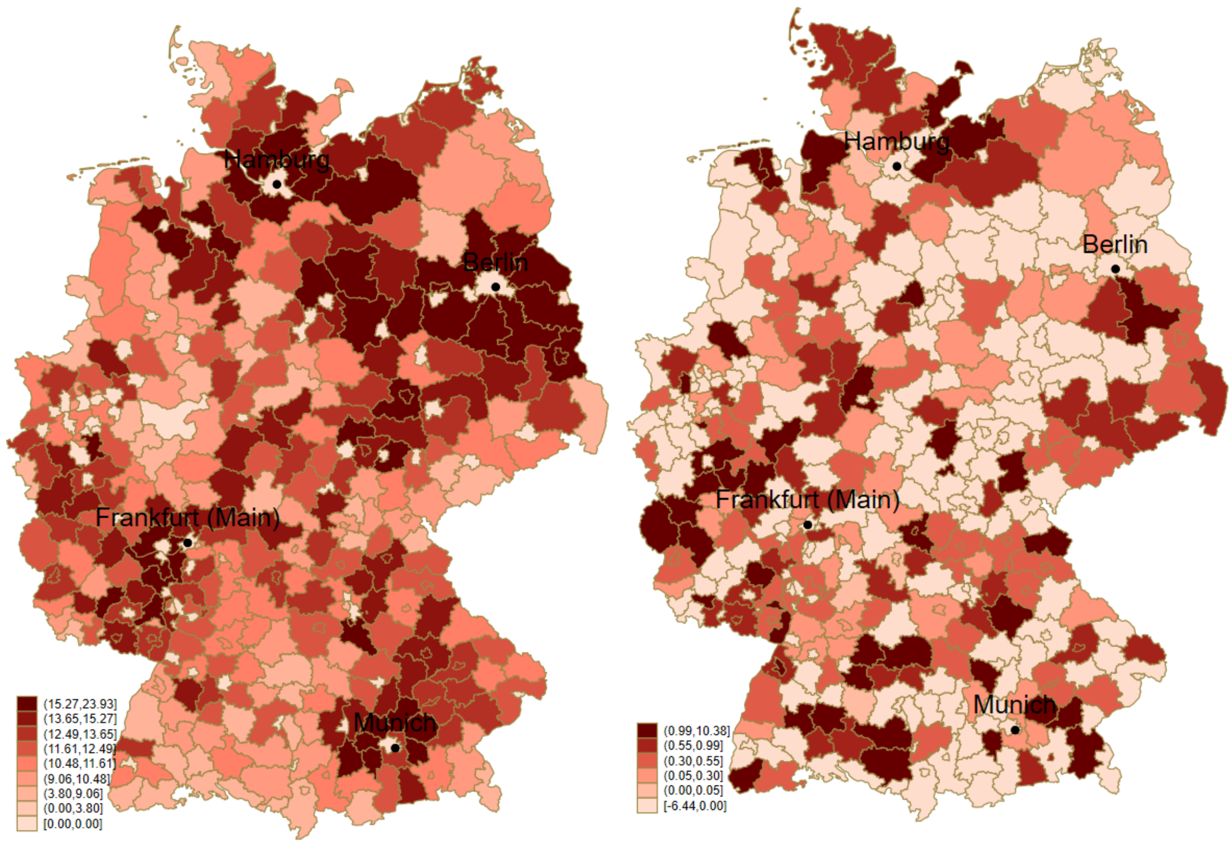



Figure 2: Evolution of Average Commuting Distances by Gender

*Notes: Commuting distances are calculated as driving distances between geographic centers of the municipality of the individual's place of residence and place of work. Source: 2 % random sample of the Integrated Employment Biographies (IEB) provided by the German Institute for Employment Research (IAB). Own computations.*

Figure 3 presents maps of median commuting distances in 2019 (first panel) and their changes between 2019 and 2022 (second panel). The first panel shows that people living in big cities have very short commuting distances, while longer commuting distances are observed in the catchment areas of major cities such as Berlin, Munich, Frankfurt, and Hamburg. The second panel reveals that the places with the largest increases in distance are not in the closest vicinity of those big cities, but rather more remote places where initial distances were relatively short. This suggests that people living in places beyond the typical commuting distance to big cities started to work there - possibly making use of the opportunity to work from home.

We utilize average rent prices at the county level collected 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. According to Mense et al. (2023) the data covers between 80 and 90 per cent of the rental housing market in Germany. Mense et al. (2023) calculated the rent per




(a) Median Commuting Distances in 2019

(b) Change in Median Commuting Distances 2019-2022

Figure 3: Median commuting distances by county

*Notes: Commuting distances are calculated as driving distances between geographic centers of the municipality of the individual's place of residence and workplace. Here, distances are aggregated to the level of 400 NUTS-3 counties. Source: 2 % random sample of the Integrated Employment Biographies (IEB) provided by the German Institute for Employment Research (IAB). Own computations.*

square meter, net of utilities and heating costs based on information on the net rent, the unit size in square meters, the postcode of the unit, the month of its first appearance, and a list of housing characteristics. 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 in the respective analyses.

Appendix Table A.1 reports summary statistics for the work-home distance and individual characteristics of the data used for the main regression analyses.

### 2.2 The indicator for the potential of working from home (HOP indicator)

We use an indicator that describes each occupation's suitability to be performed remotely, the so called HOP indicator. The indicator is proposed by Bruns et al. (2023).[4]

The 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. (2021), and Arntz et al. (2020)); this makes our indicator less vulnerable to endogeneity issues. Secondly, the indicator relies on explicitly formulated working conditions 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. BERUFENET[5] 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. BERUFENET distinguishes 73 working conditions; on average (median), it reports 9.2 working conditions per occupation, with a minimum of 1 working condition for "voice actors" ("work in ateliers or studios") and a maximum of 24 working conditions for "master agricultural machinery mechanics". The working conditions include requirements on multiple dimensions: social distance, work place, physical or cognitive burden, and requirements on the working time distribution.

Short social distances and specific work place requirements may imply that WFH is not possible. Physical or cognitive burdens signal that tasks can only be performed at the

[4]Our description relies on this study that is not yet published; we deliver further details on request.
[5]http://berufenet.arbeitsagentur.de

work place. In addition, specific restrictions on the working time distribution may have an impact on whether a job can be performed remotely or not. Therefore, those working condition categories are relevant for the potential of occupations to be performed from home.

Bruns et al. (2023) classified the working conditions allowing WFH or not. For this purpose, each author carried out an independent assignment before a joint evaluation of the results and then they created a consensus on classifications where they initially did not agree. This represents an established procedure to achieve inter-coder reliability that also withstands further examinations (Artstein and Poesio (2008); Mayring (2014, p. 42)). The classification was based on the criteria of whether the individual conditions are more conducive (as-signed value "+1"), "ambiguous" (value "0") or more of a hindrance (value "-1") for WFH. Bruns et al. (2023) consider a category "ambiguous", due to some working conditions for which it is not fully clear whether they are relevant for WFH or not. This is, e.g., the case for all conditions in the category "working time distribution". Requirements on the working time distribution, like seasonal work, may imply for some jobs that they cannot be performed from home (like service staff in a hotel at the Baltic sea) but for other jobs it would be possible (at least partly for an event planner in the same hotel). Another reason is that Bruns et al. (2023) assume that the combination of working conditions for each job has an impact on the WFH potential, since this potential should decrease for jobs with a combination of some working conditions that are conducive for WFH and a larger number of working conditions that are ambiguous compared with jobs with the same number of conducive conditions but with a smaller number of ambiguous conditions.

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]

We check the validity of our indicator by examining its correlation with the actual use of WFH as reported by Mergener (2020)[7] at the two digit level of occupations (occupational main groups) and based on the same data also used by Arntz et al. (2020); Alipour

[6]Bruns et al. (2023) 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.

[7]See table A2 in the online Appendix of ibid.

et al. (2021) – the BIBB/BAuA Employment Survey of the Working Population on Qualification and Working Conditions in Germany 2018 (BIBB/BAuA-ETB 2018, Hall and Rohrbach-Schmidt, 2020). For this purpose, we aggregated the HOP indicator at the level of occupational main groups weighted by the number of employees.

We find a strong positive correlation (0.89) of the HOP indicator and the use of WFH. Figure 4 shows the scatter plot with value pairs of the HOP indicator and the average use of WFH for each occupational main group illustrating the value pairs distributed across both theoretical value bands between 0 and 1 and a positive regression line.

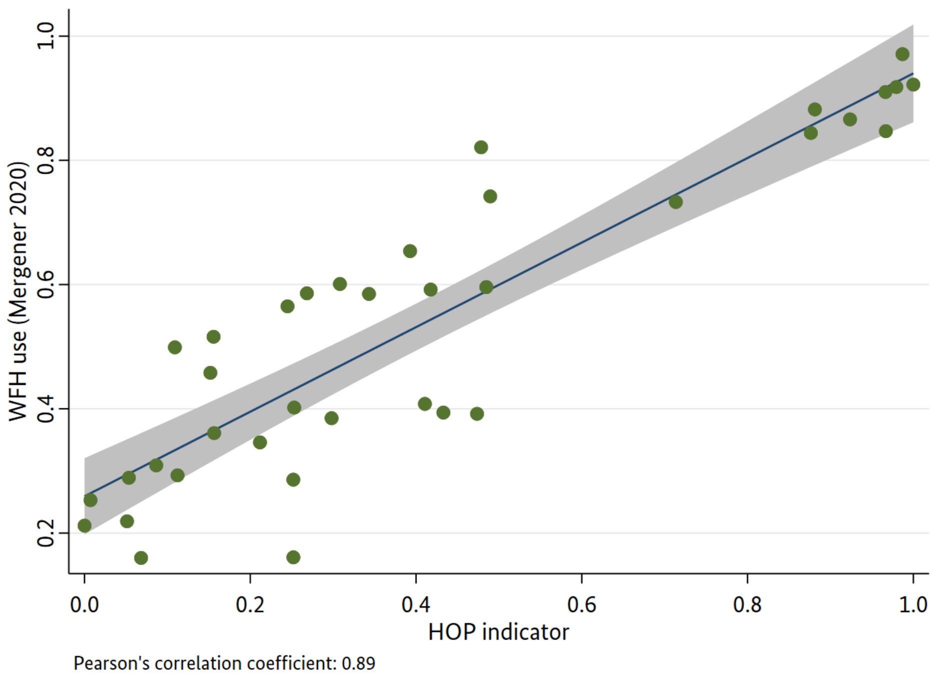
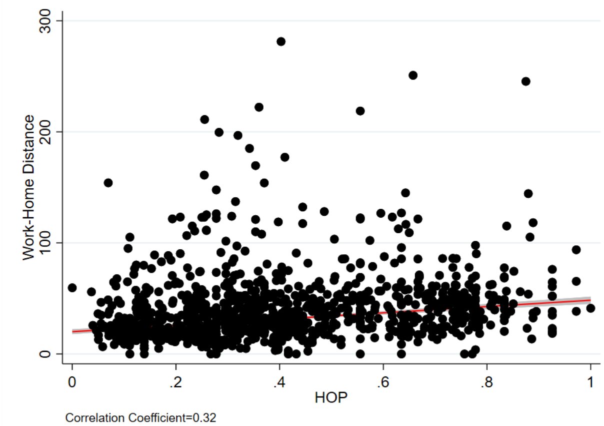


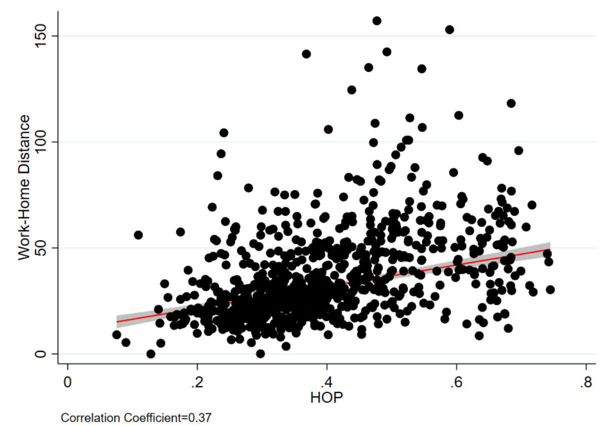

Figure 4: The actual use versus the potential of working from home (HOP)

*Notes: The values of the actual use of working from home at the level of occupational main groups (2-digit code of the German classification of occupations 2010) are taken from table A2 in the online Appendix of Mergener (2020) (https://kzfss.uni-koeln.de/sites/kzfss/pdf/Mergener.pdf). The indicator for the WFH potential (HOP) is based on the working conditions that are reported in BERUFENET. The regression line is based on a simple linear model that regresses the actual use of working from home on HOP and includes a constant. The grey area represent 95%-confidence intervals, based on standard errors. Pearson's correlation coefficient of the actual use of working from home and HOP is reported below the graph.*
*Source: Mergener (2020). BERUFENET. Own computations.*

Finally, we report descriptive evidence that workers in occupations with a higher HOP tend to have longer commuting distances. Figure 5 reports scatter plots of average commuting distances and HOP-values, aggregated at the 5-digit occupation (first panel) or 5-digit industry level (second panel).[8] The positive correlation is in line with the notion that workers in high-HOP can have, ceteris paribus, greater distances between residence and workplace and still achieve the same utility as workers in low-HOP occupations.




(a) By Occupation




(b) By Industry

Figure 5: HOP and average work-home distance

*Notes: The figure reports the average commuting distance and HOP for each 5-digit occupation (first panel) or 5-digit industry (second panel), between 2016-2019. Commuting distances are calculated as driving distances between geographic centers of the municipality of the individual's place of residence and workplace. The indicator for the WFH potential (HOP) is based on the working conditions that are reported in BERUFENET.*
*Source: 2 % random sample of the Integrated Employment Biographies (IEB) provided by the German Institute for Employment Research (IAB). BERUFENET. Own computations.*

Even though firms that offer jobs having potential to be done from home could in principle be located anywhere, Figure 6 reveals a tight positive correlation between a county's average HOP and its population size. This is in line with Althoff et al. (2022), who also show that jobs with high remote work potential are concentrated in big cities.[9] This "City Paradox" implies that firms could potentially save expenditures for labor and land by moving away from cities. However, cities seem to offer productive amenities that have led firms to locate there despite those higher costs. WFH offers new possibilities to optimize location choices of both, firms and workers.

[8]In Appendix Figure A.2, we also report the correlation at 3-digit occupation and industry levels.
[9]Appendix Figure A.3 shows a map that also emphasizes that high values of HOP are concentrated in bigger cities.

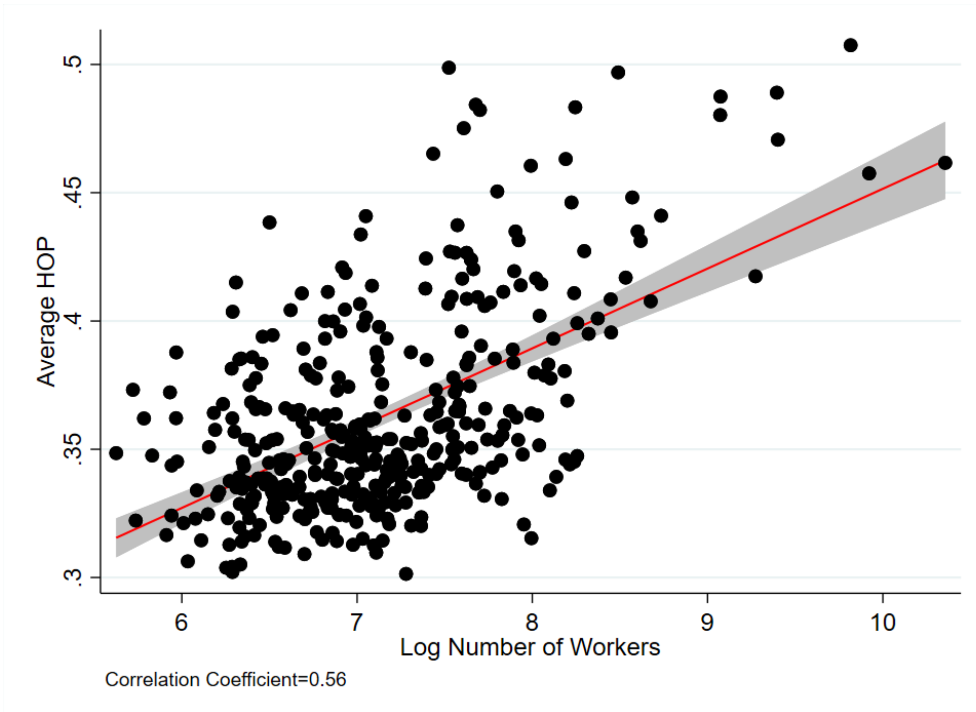



Figure 6: Number of workers and average HOP by counties

*Notes: The figure reports the logarithmic number of workers and the average indicator for the WFH potential (HOP) by counties. The latter is the arithmetic mean of HOP across all occupations weighted by the respective number of workers in those occupations in each county.*
*Source: 2 % random sample of the Integrated Employment Biographies (IEB) provided by the German Institute for Employment Research (IAB). BERUFENET. Own computations.*

## 3 Empirical Strategy

Whether and how individuals commute can be handled as job attribute. Commuting may induce disutility, the individual commuting costs $\tau$ that accrue during a certain time interval $\Omega$ (say, a month or a week) are a function of the individual's costs per unit of distance $c$ (due to expenditures for gasoline or public transit fares and opportunity costs for the time spent commuting), the distance between residence and workplace $d$, and the number of trips taken during the time interval $\omega$. For an individual to accept a job offer at a certain distance, either higher wages (Van den Berg and Gorter, 1997) and/or housing costs (Brueckner, 1987) must serve as a compensating differential. Using the notation of Le Barbanchon et al. (2020), consider the utility of an individual with housing costs $H$, being employed in a job with wage $W$: $u(W, H, \tau) = log(W) - log(H) - \alpha\tau(c, d, \frac{\omega}{\Omega})$, where $\alpha$ is the willingness to pay for a shorter commute. Defining $rU$, the flow value of unemployment (where housing may be paid for by the unemployment insurance), a job seeker accepts all job offers, where $log(W) - \alpha\tau(c, d, \frac{\omega}{\Omega}) > rU + log(H)$. This implies that an individual at a given residence, with given commuting costs per unit of distance, and a given willingness to pay to avoid commuting, who is offered a job with wage $W$ and the necessity to commute $\omega$ times per time interval will have a certain reservation radius $\overline{d}(W, \frac{\omega}{\Omega})$, within which the workplace must lie in order to accept the offer.

The opportunity to work from home reduces the required number of commuting trips $\omega$ and therefore the commuting costs $\tau$ (Aksoy et al., 2023). This implies that the reservation radius $\overline{d}(W, \frac{\omega}{\Omega})$ increases for smaller $\omega$. 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. Theoretically, the fraction of days commuted $(\frac{\omega}{\Omega})$ is negatively correlated with the job's WFH potential. Put differently, jobs with a high HOP should have a larger reservation radius, which is in line with the average distances illustrated in Figure 5.

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 dramatically during the Covid-19 pandemic, which created an exogenous shock to the acceptability of WFH, including technical and organizational prerequisites. We use this as a natural experiment that creates variation in $\omega$ in order to estimate changes in work-home distance connected to the WFH potential. Workers in occupations with a high WFH potential should have, on average, higher increases in their work-home distances. In our empirical analysis, we explore the relationship of the work-home distances and WFH potential using a difference-in-differences approach.

Our main regression model is illustrated in Equation 1. The outcome variable is $d_{jt}$, the work-home 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 $t$. We capture changes in the fraction of days not commuted by interacting $HOP_{o(j,t)}$ 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 $s = 0$.

$$d_{jt} = \gamma HOP_{o(j,t)} + \sum_{s=-50, s\neq 0}^{33} \Big[\beta_s HOP_{o(j,t)} \mathbb{1}(t=s)\Big] + \delta_t + \psi_{o(j,t)} + \phi_{s(j,t)} + \nu_{ind(j,t)} + \beta X_{jt} + \epsilon_{jt} \tag{1}$$

where $\delta_t$ is a vector of 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, $\epsilon_{jt}$ are the errors and $X_{jt}$ includes controls: age, age square, gender, and tenure in the job.

The coefficient $\gamma$ is the expected difference in commuting distances comparing workers in different 5-digit occupation within the same 3-digit occupation group in the base period March 2020. The interaction terms of HOP and month dummies allow that this HOP effect can differ over time. The treatment effects for the months during and after the shock are given by $\beta_1, \beta_2, \ldots, \beta_{33}$, which represent the months April 2020 through December 2022. The $\beta$-coefficients with negative subscripts represent the months from January 2016 through February 2020 and capture possible pre-trends. 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 years by using the two-way clustered standard error option provided by Correia (2016).

In order to explain the nature of the approach, assume that there are two industries; the first industry includes jobs with full and the second with no WFH potential. There is a single treatment date. In such a setting, we can use classic difference-in-difference estimation. The identification is based on the parallel trends assumption: The development of the outcome would not have differed between the groups without the treatment. This can at least be made plausible considering the data for the pre-treatment period. In reality, the Covid-19 shock affected all occupations, but the strength varies: Indeed, we have a 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. Logically, the procedure represents a difference-in-difference approach with continuous treatment intensity rather than binary treatment.[10]

In further analyses, we estimate a more parsimonious model as shown in Equation 2.

[10]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).

Here, we collapse the monthly interactions to the level of calendar years. $\beta_{2020}$, $\beta_{2021}$ and $\beta_{2022}$ represent the differential HOP-effects 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.

$$d_{jt} = \gamma HOP_{o(j,t)} + \sum_{y=2020}^{2022} \left[ \beta_y HOP_{o(j,t)} \mathbb{1}(year(t) = y) \right] + \delta_t + \psi_{o(j,t)} + \phi_{s(j,t)} + \nu_{ind(j,t)} + \beta X_{jt} + \epsilon_{jt} \tag{2}$$

# 4 Results

## 4.1 Main Results

For our analyses, we use the sample between 2016 and 2022. Work-home distance has a long run increasing trend as shown in Figure 2. In order to eliminate the potential confounding effect of this long term trend, we focus on a sample for recent years (2016-2022), however, all our results are robust to year selection. In order to capture business cycle effects, our empirical specification includes month fixed effects, and to capture differential preferences with respect to jobs, we use occupation and industry fixed effects. Our control variables include gender, age, and tenure in a job.

Figure 7 shows the changing effect of WFH potential on work-home distance estimated for every month between 2016 and 2022. Note that people who hold jobs with higher WFH potential have higher work-home distance on average (See Figure 5). This effect is captured by the variable $HOP_{o(j,t)}$ in Equation 1. In Figure 7, we plot the interaction terms of HOP with month dummies. Hence, interaction terms capture the changing effect of HOP on distance relative to March 2020 (the omitted reference category). The figure reveals that the way HOP is associated with commuting was stable in the four years preceding the Covid-19 pandemic.[11] The coefficients in 2020 do not deviate from

[11] The reason for the observed seasonality is the fact that if there is a change in the home address during the contract period, this is not registered until the beginning of the upcoming year. Hence, if a person starts a job, the current address is registered. If the person moves to a new location after the start of the contract, it is not registered until January in the following year. Therefore, the effect is growing between January and December and drops in January of the following year when the move of the person has been registered. Consequently, this delay in the address registration creates a downward bias in our results as our data does not cover some of the address changes in 2022. We conduct a robustness check to validate

this pattern; if anything, each coefficient lies below the average of the corresponding months in the previous years. The early months of the Covid-19 pandemic were hallmarked by huge uncertainty. It appears plausible that in this environment, people were more likely to behave conservatively without speculating when the pandemic would end and whether WFH would be retained at the current level. This uncertainty was markedly reduced when development of several vaccines against the coronavirus was finished in November 2020 and approval was granted by authorities in the USA and the EU in December 2020. The coefficients in 2021 clearly show that the association of HOP and distance increased significantly relative to other months in the sample. In 2022, this development continued with a slightly lower gradient.[12]

this hypothesis based on the adjustment of distances by utilizing information of the timing of job switches. We find that the seasonality disappears with the adjustment. See Appendix B for details.

[12] Appendix Figure A.5 shows that the same pattern also holds when commuting distance is specified as logarithmic distance.

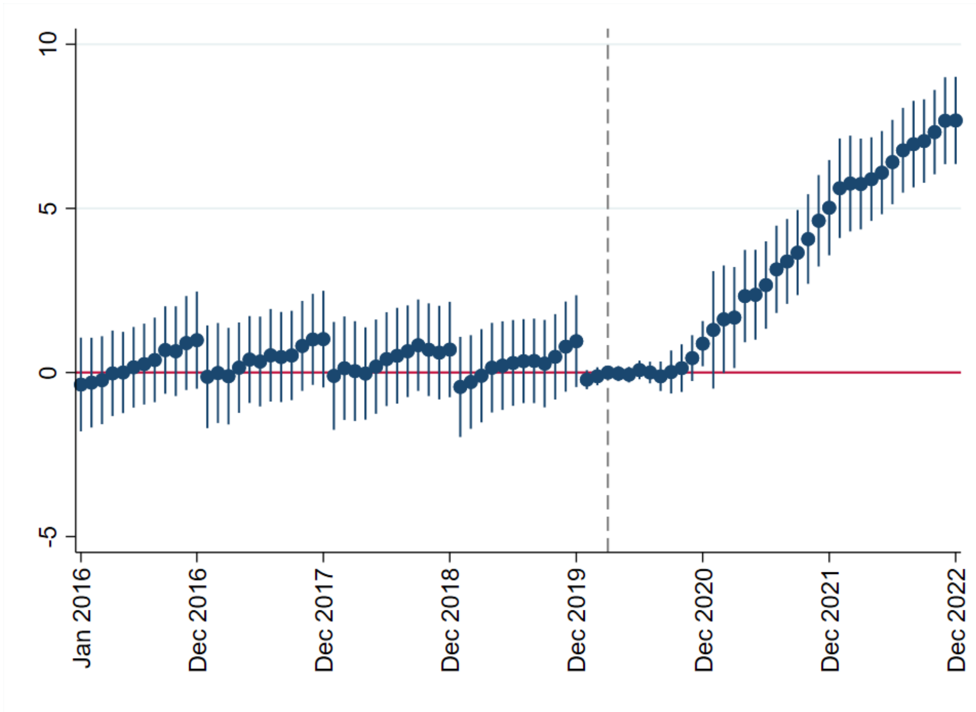



Figure 7: Effect of HOP on Work-Home Distance

*Notes: The figure reports the results of a regression of individual commuting distances on HOP, year-month-dummies and interactions of these variables (along with control variables). The outcome is work-home distances, calculated as driving distances between geographic centers of the municipality of the individual's place of residence and 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. 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.*

In Table 1, we show the effect of pandemic years and HOP on work-home distance from Equation 2. In columns 1–3, the dependent variable is the commuting distance in kilometers, in columns 4–6, we use the logarithm of the commuting 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 Figure 7. Besides the exceptional degree of uncertainty, WFH was perceived more as a necessity than an opportunity and apparently has not driven location decisions of commuters. 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 now take up jobs at locations that are further away than before the pandemic.[13] However, although minor, the significantly positive coefficient for existing jobs also shows that some people with high HOP moved their home to places further away while still holding their jobs. In 2022, the effects increased further. For existing jobs, the effect more than doubles compared to 2021. Evidently, relocation takes time for deciding, organizing, and implementing. Therefore, the full effect can be expected to come with a delay. We confirm this by separating the effects for firm and residence movers. Figure 8 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 place of residence for each year of the entire observation period. The effect of HOP is clearly visible for both firm and residence changers in 2021 and 2022. In the latter year, the effect on residence changers is significantly higher than on firm changers. In line with some anecdotal evidence, at least some people appear to have reacted systematically to Covid and the new possibility of WFH by moving out of larger cities at least in the medium run. Since moving residence is a major act, this effect is quite forceful but the number of movers is smaller than the number of firm changers, and hence, residence movers contribute only little to the overall effect.

The results for the logarithmic commuting distance in columns 4–6 of Table 1 are qualitatively similar but quantitatively around 60 percent smaller when evaluated at the mean compared to the results for the commuting distance in absolute terms. This indicates that long commuting distances, such as when (tele-)commuting between cities of from relatively remote regions, are an important margin of adjustment.

[13]We cannot rule out that form changers endogenously move to higher HOP occupations as a response to the pandemic. However, Appendix Figure A.4 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 1: Main Regression Results: Work-Home Distance

| | Dependent variable: | | | | | |
|---|---|---|---|---|---|---|
| | Commuting distance | | | ln commuting distance | | |
| | All jobs | New jobs | Existing jobs | All jobs | New jobs | Existing jobs |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| HOP | 21.083* | 32.313** | 19.045* | 0.797*** | 0.987*** | 0.767*** |
| | (0.019) | (0.010) | (0.025) | (0.001) | (0.001) | (0.001) |
| HOP × dummy, 1=2020 | -0.247 | -3.027*** | 0.438 | -0.011 | -0.074*** | 0.001 |
| | (0.480) | (0.000) | (0.220) | (0.168) | (0.000) | (0.919) |
| HOP × dummy, 1=2021 | 2.676*** | 9.614*** | 1.722** | 0.028** | 0.086*** | 0.020* |
| | (0.000) | (0.000) | (0.001) | (0.002) | (0.000) | (0.019) |
| HOP × dummy, 1=2022 | 6.258*** | 13.117*** | 4.591*** | 0.083*** | 0.159*** | 0.062*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| N | 57,955,352 | 11,369,957 | 46,585,395 | 57,955,352 | 11,369,957 | 46,585,395 |
| R2 | 0.077 | 0.070 | 0.080 | 0.113 | 0.107 | 0.114 |

*Notes: Regression period covers all jobs between 2016-2022, people who worked at least 10 days in a month are included. 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.*

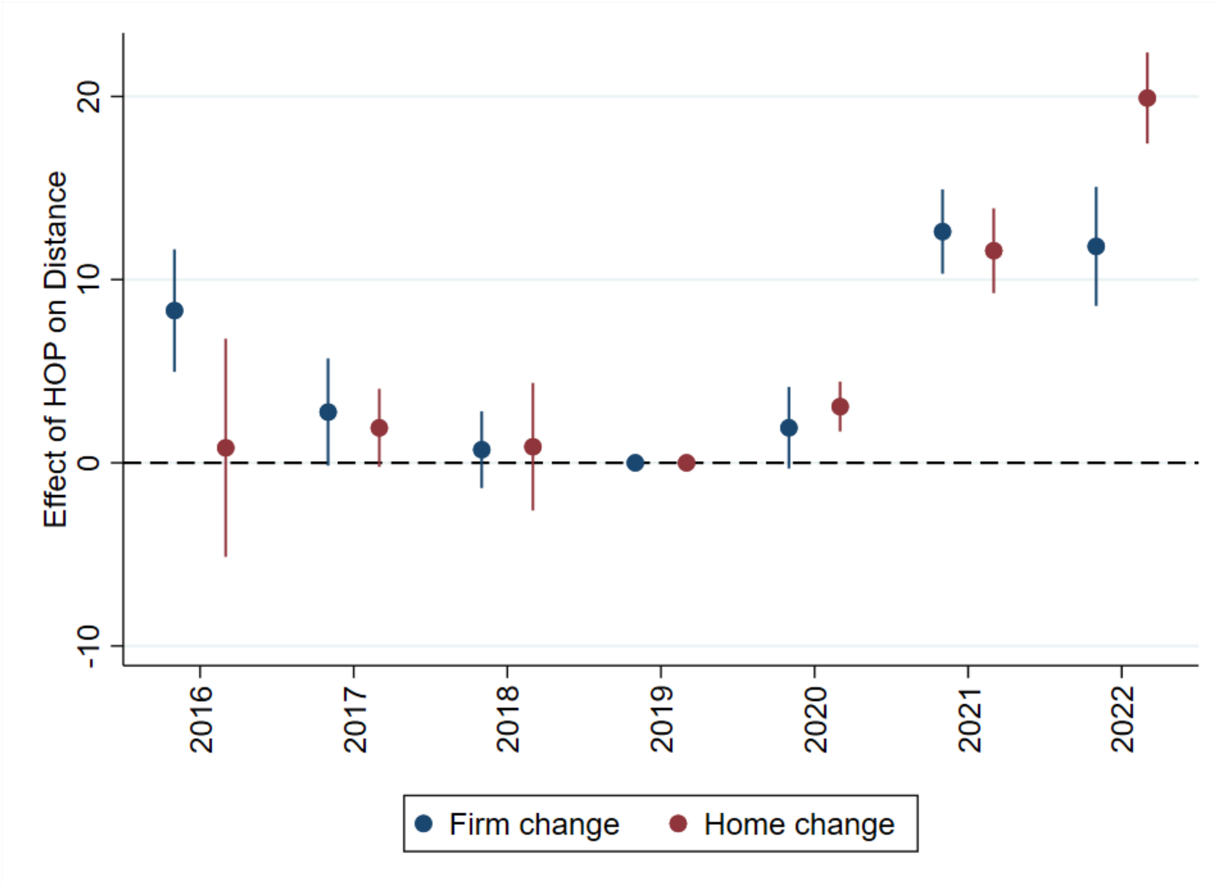



Figure 8: Commuting Distance and HOP among Movers

*Notes: The figure reports the results of a regression model that separates the effects of HOP on individual commuting behavior for workers who have either recently moved firm or place of living. The outcome is commuting distance, calculated as driving distances between geographic centers of the municipality of the individual's place of living and place of work. 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.*

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 21 km longer before the pandemic. This is quite large, given that the median commuting distance in the sample is 8.69m. For two occupations that differ by one standard deviation of HOP (0.23), we expect commuting distances to differ by about 4.8 kilometers. In 2021 and 2022, the longer commuting distances associated with HOP were even more pronounced and increase by 13 to 30 percent of the initial HOP effect. This increase is particularly driven by workers who have recently started their jobs (columns 2 and 5). With each standard deviation of the HOP difference, workers who started their job in 2021 or 2022 commuted two to three kilometers further, which corresponds to 30 and 40 percent of the baseline HOP effect on job starters before the pandemic.

### 4.2 The Geography of Telecommuting

Next, we explore how working from home affects the economic geography of the German labor market. In Table 2, 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 with HOP and the (post-)pandemic years. Column 1 repeats the result of column 5 from Table 1. Column 2 reveals that people commuting to bigger cities have shorter commuting distances. This reflects the stylized fact reported in panel (a) of Figure 3: commuting distances are shortest for the large number of workers who live and work in big cities. Interestingly, column 3 shows that this pattern is a little less 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. Workers in high-HOP occupations had lower commuting distances in 2020 and before. 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 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 the year 2021 indicates that this tendency was reversed in 2021 and 2022. 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 2: Regression Results: Work-Home Distance in Big Cities

| | Dependent variable: ln commuting distance | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| HOP | 0.987*** | 1.034*** | 1.039*** | 1.101*** |
| | (0.001) | (0.001) | (0.001) | (0.001) |
| HOP × dummy, 1=2020 | -0.074*** | -0.075*** | -0.078*** | -0.045* |
| | (0.000) | (0.000) | (0.000) | (0.016) |
| HOP × dummy, 1=2021 | 0.086*** | 0.088*** | 0.078*** | 0.024 |
| | (0.000) | (0.000) | (0.000) | (0.223) |
| HOP × dummy, 1=2022 | 0.159*** | 0.159*** | 0.136*** | 0.073* |
| | (0.000) | (0.000) | (0.000) | (0.018) |
| dummy, 1=Big City | | -0.375*** | -0.388*** | -0.333*** |
| | | (0.000) | (0.000) | (0.000) |
| dummy, 1=Big City× dummy, 1=2020 | | | 0.008 | 0.036* |
| | | | (0.315) | (0.048) |
| dummy, 1=Big City× dummy, 1=2021 | | | 0.023** | -0.022 |
| | | | (0.003) | (0.140) |
| dummy, 1=Big City× dummy, 1=2022 | | | 0.057*** | 0.005 |
| | | | (0.000) | (0.797) |
| HOP×dummy, 1=Big City | | | | -0.151 |
| | | | | (0.184) |
| HOP×dummy, 1=Big City× dummy, 1=2020 | | | | -0.072* |
| | | | | (0.016) |
| HOP×dummy, 1=Big City× dummy, 1=2021 | | | | 0.120** |
| | | | | (0.003) |
| HOP×dummy, 1=Big City× dummy, 1=2022 | | | | 0.141*** |
| | | | | (0.001) |
| N | 11,369,957 | 11,369,957 | 11,369,957 | 11,369,957 |
| R2 | 0.107 | 0.113 | 0.113 | 0.113 |

*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. 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.*

Labor markets of big cities provide several advantages, including the abundant availability of a qualified workforce (Behrens et al., 2014). One opportunity provided by

WFH is that firms in remote regions can potentially access urban labor markets – by offering WFH jobs to qualified city dwellers who may be reluctant to move out of their cities for job reasons. We examine this by regressing the median rent of the workplace and residence county on our explanatory variables in Table 3. The intuition of this analysis is that rents represent the size and attractiveness of locations. Again, we focus on workers who recently started their job. We begin by measuring rents in current prices: the rent level at the workplace county in column 1, of the residence county in 2, and the difference of the two in 3. The positive coefficients of HOP in columns 1 and 2 confirm that high-HOP jobs and the residences of the people holding those jobs were concentrated in more expensive housing markets, that is, in big cities and their surroundings. In 2020 and 2021, this tendency is reduced due to the increased practice of WFH: New jobs and the people holding them are still more likely to be located in more expensive housing markets, but to a lesser extent. This would suggest that WFH is becoming an increasingly pervasive phenomenon that is not restricted to big cities. However, both coefficients become positive in 2022, implying that the most recent trends are again driven by plants and workers located in more expensive housing markets.

Table 3: Regression Results: Work-Home Rent Difference

| | Dependent variable: | | | | | |
|---|---|---|---|---|---|---|
| | Rent at Current Prices | | | Rent at Fixed 2018 Prices | | |
| | Workplace | Residence | Diff | Workplace | Residence | Diff |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| HOP | 0.063*** | 0.059*** | 0.004 | 0.057*** | 0.056*** | 0.002 |
| | (0.000) | (0.000) | (0.462) | (0.000) | (0.000) | (0.765) |
| HOPX2020 | -0.011*** | -0.005** | -0.006*** | -0.000 | 0.000 | -0.000 |
| | (0.000) | (0.002) | (0.000) | (0.950) | (0.804) | (0.385) |
| HOPX2021 | -0.024*** | -0.016*** | -0.008*** | 0.001 | -0.002* | 0.003*** |
| | (0.000) | (0.000) | (0.000) | (0.435) | (0.033) | (0.000) |
| HOPX2022 | 0.001 | 0.002 | -0.002** | 0.002* | -0.004** | 0.006*** |
| | (0.646) | (0.103) | (0.002) | (0.032) | (0.002) | (0.000) |
| N | 57893370 | 57893370 | 57893370 | 57893370 | 57893370 | 57893370 |
| R2 | 0.587 | 0.511 | 0.044 | 0.572 | 0.495 | 0.048 |

*Notes: Regression period covers all jobs 2016-2022, people who worked at least 10 days in a month are included. 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.*

In this analysis, variation of the outcome variables comes from two sources: Geographical variation of where people work and live and variation over time of the housing prices of a given county. Indeed, Figure 9 shows that the rent prices in big cities evolve differently than in other cities; we observe a convergence in rent prices in nominal terms after the pandemic, which might potentially be endogenous to the movement of people. To eliminate this source of variation, we only use 2018 fixed rent prices in subsequent analyses.

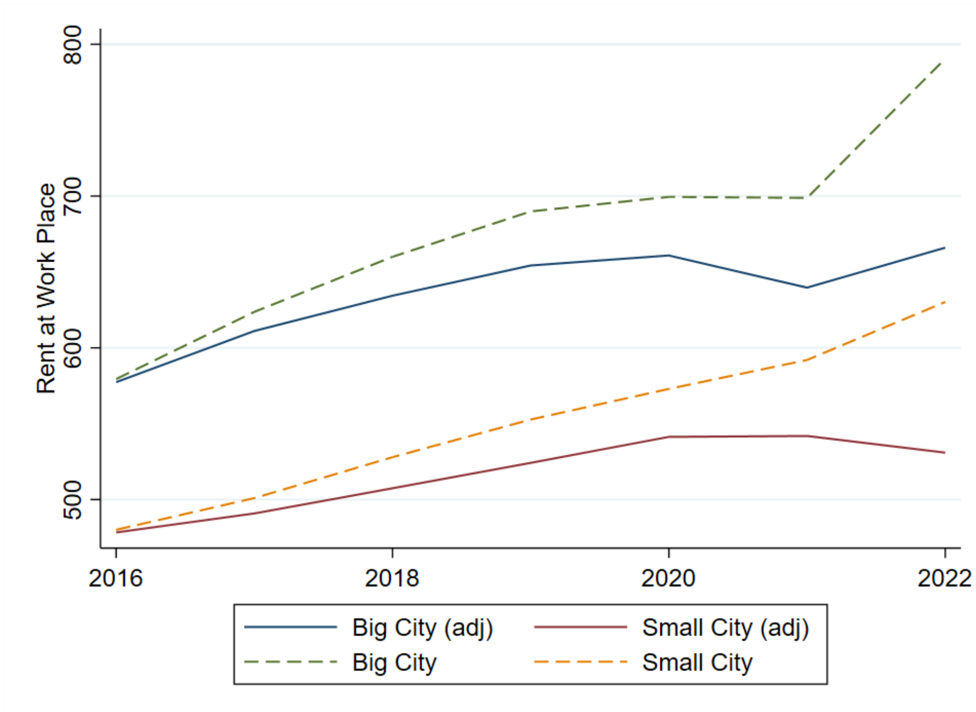



Figure 9: Rent Prices in Big and Small Cities

*Notes: This figure reports the evolution of average rent prices (weighted by the number of workers) for dwellings in big versus small cities (more or less than 100,000 inhabitants). The dashed lines represent nominal prices and the solid lines real prices in 2018.*
*Source: Average rent prices at the county level were provided by Mense et al. (2023).*

Columns 4 to 6 in Table 3 conform to 1-3 but use rents at fixed prices. Here, differences between the pre-covid period and 2020 or 2021 are mostly small and insignificant. By contrast, HOP has a positive effect on the rent price at the workplace in 2022, but a negative effect at the place of residence. Logically, 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 Figure 10 confirms that while there are substantial fluctuations in the HOP effect on the rent difference at current prices, the difference at fixed prices was flat until 2020. Afterwards, we see a striking increase in 2021 and 2022.

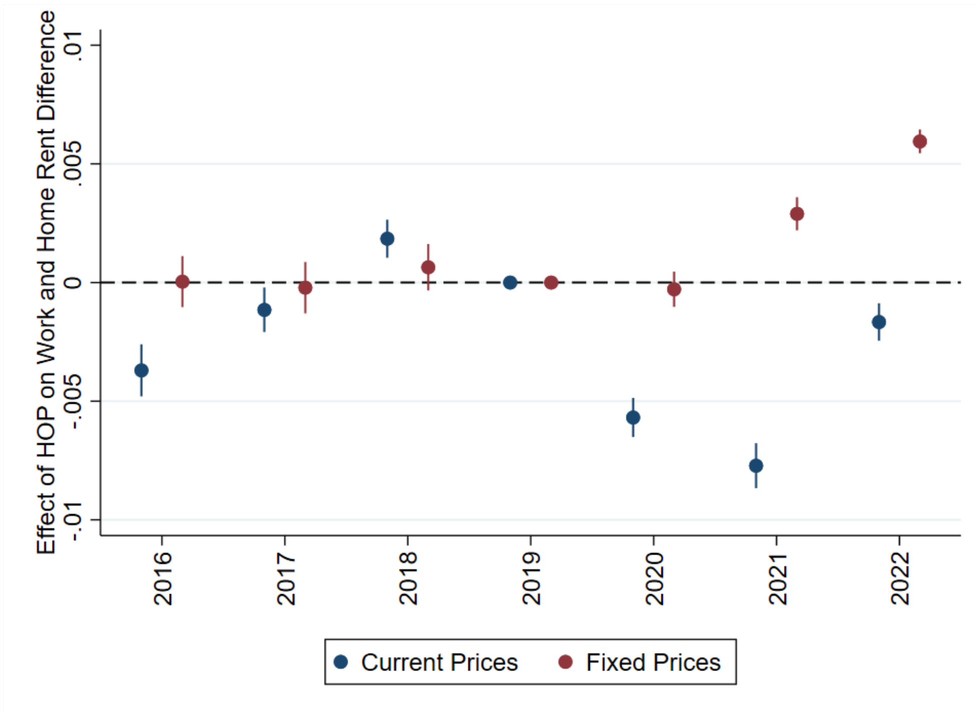
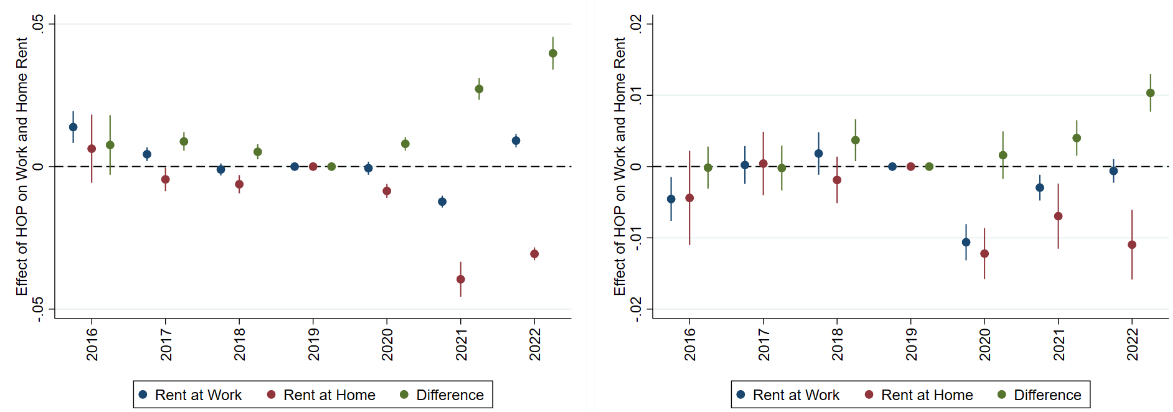



Figure 10: HOP and Rent Difference between the Workplace and Place of Residence

*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 median rent per square meter of the county of the individual's workplace and place of residence at 2018 fixed prices. 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. 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.*

Having established that WFH had an effect on location decisions, it is interesting to see to what extend this stems from workers who have changed jobs versus workers who have changed residences. Figure 11 reveals the difference between home changers and firm changers. The first panel confirms that the HOP effect on the rent at the place of residence was substantially negative for home changers, while no clear effect results for the rent at the workplace. In the same line, the effect on the rent at the place of residence is negative for firm changers, while there is only a non-persistent deviation for the rent at the workplace in 2020. In conclusion, due to WFH options, workers either moved to counties or switched jobs without moving to more expensive counties as they would have done before the pandemic. This implies that the firms that mostly benefit from the consequences of increased WFH are located in big cities. Those firms have reaped the productive amenities of cities before but were likely restricted by tight housing markets in and around those cities. Allowing their workers to telecommute at least for some days per week has alleviated labor shortages by increasing those firms' catchment areas. By contrast, firms in rural counties do not seem to benefit from this trend either because they do not offer jobs with sufficiently high HOP or because they do not allow their workers to telecommute even if their job could be done from home.




(a) Home Changers

(b) Firm Changers

Figure 11: HOP and Rent at Workplace and Place of Residence

*Notes: The figure reports the results of a regression of rents at the workplace and residence counties on HOP, year-month-dummies and interactions of these variables (along with control variables). The outcomes are median rent per square meter of the county of the individual's workplace and place of residence at 2018 fixed prices, and the difference between those rents. 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. 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 district level are provided by Mense et al. (2023). Own computations.*

### 4.3 Gender Differences

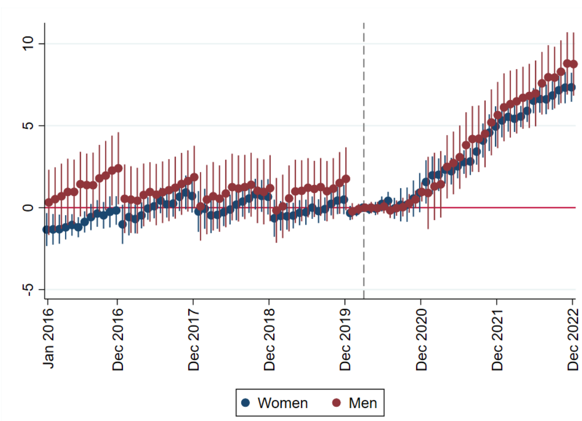
Commuting has a profound gender dimension. Women work on average much closer to where they live (see Figure 2) and have a higher willingness to pay for a shorter commute, which means that they require a higher wage in order to commute further (Le Barbanchon et al., 2020). Since this restricts the number 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. (2023), 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 Figure 12, we report the results of our main analyses separately for women and men. The effects of HOP on work-home distances are moderately but not significantly larger for women than for men in 2022. At least to some extent, women appear to make use of HOP more strongly than men to work at plants that used to be out of reach in the pre-covid period and therefore reduce the gender commuting gap. However, the figure suggests that women have already used WFH to reach more distant jobs even before the covid pandemic slightly but again not significantly more than men. By contrast, the second panel of Figure 12 indicates that the effect of HOP on fixed 2018 rent differences between county of work and county of residences is more pronounced for men in 2022. This suggests that it is men who benefit most from the possibility to telecommute and reach employers in more remote high-rent region from their comparatively lower rent residences.

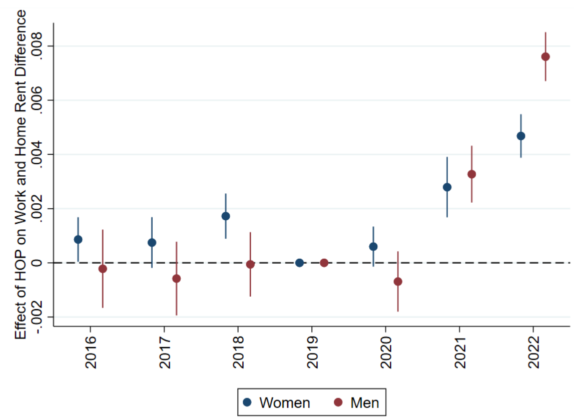
## 5 Conclusion

In this study, we investigate changes in commuting 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.




(a) Work-Home Distance




(b) Work-Home Rent Difference

Figure 12: 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 versus residence counties (Panel b) on HOP, year-month-dummies and interactions of these variables (along with control variables). The outcomes are work-home distances, calculated as driving distances between geographic centers of the municipality of the individual's place of residence and workplace (Panel a) and the difference median rent per square meter of the county of the individual's 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: 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.*

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.

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# Appendix

## A Data

The analysis covers the job spells between 2016 and 2022. A monthly dataset is constructed in order to make the job spells representative over the year to account for seasonality. The unit of observation is jobs; i.e., some individuals have more than one job at a given time. We do not include people who worked less than 10 days in a given month. In case a person has multiple jobs at the same time, we keep only the main job, which we define main as the job with the highest tenure. We regard this as prudent, since commuting to secondary jobs might entail mechanisms that are more complex compared to what we lay out in Section 3. However, keeping all jobs does not alter our results in any qualitative way.

Table A.1 reports summary statistics for the distance, HOP, and individual characteristics of the data used for the main regression analyses.

Table A.1: Descriptive Statistics

| | mean | sd | min | max | p25 | p50 | p75 |
|---|---|---|---|---|---|---|---|
| Age | 43.110 | 13.815 | 0 | 117 | 32 | 44 | 54 |
| Female | .472 | .499 | 0 | 1 | 0 | 0 | 1 |
| Year | 2019.019 | 1.994 | 2016 | 2022 | 2017 | 2019 | 2021 |
| Distance | 31.490 | 86.391 | 0 | 1082.244 | 0 | 8.585 | 23.211 |
| Tenure in a job (days) | 85.940 | 86.378 | 1 | 546 | 17 | 52 | 133 |
| Big City | .365 | .481 | 0 | 1 | 0 | 0 | 1 |
| Median rent at home kreis | 583.013 | 190.169 | 275 | 1320 | 449 | 560 | 695 |
| Median rent at work kreis | 597.719 | 200.171 | 275 | 1320 | 450 | 574.19 | 700 |
| Rent Difference (home-work) | 13.773 | 98.469 | -929.351 | 953.058 | 0 | 0 | 0 |
| HOP | .388 | .233 | 0 | 1 | .190 | .311 | .606 |
| Firm Change | .023 | .150 | 0 | 1 | 0 | 0 | 0 |
| Home Change | .004 | .066 | 0 | 1 | 0 | 0 | 0 |
| HOP Change | .000 | .031 | -.926 | .926 | 0 | 0 | 0 |
| Observations | 57,955,353 | | | | | | |

*Notes: This table reports summary statistics of the data used in the regression analyses.*

## B Adjusted distances

We discussed that the seasonality in Figure 7 might be due to the fact that residence changes are only recorded in January if they occur after the start of a new job. In order to validate this hypothesis, we make an adjustment; i.e., if a person starts a new job during the year and we see a residence location change in next January, we correct all previous months since the job start with the new address. Figure A.1 shows that it is indeed responsible from the seasonality; the correction removes seasonality while the magnitudes of coefficients remain unchanged.

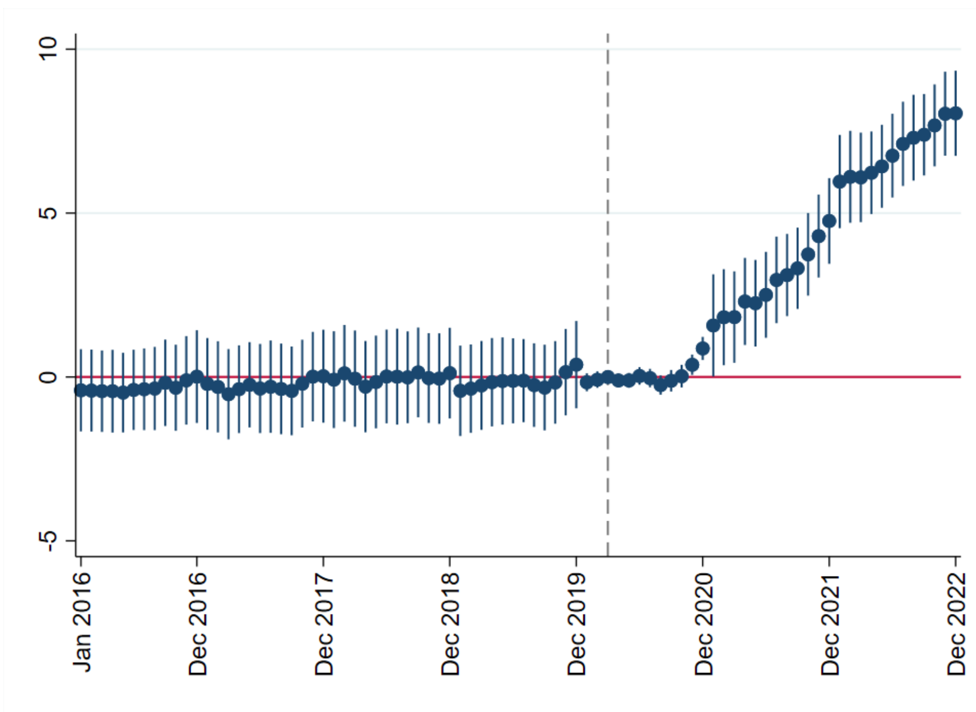
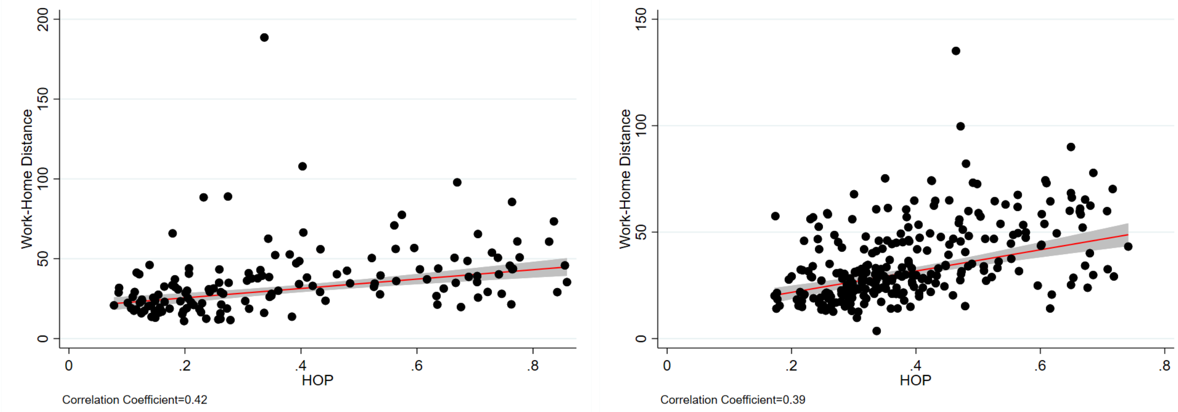



Figure A.1: Effect of HOP on Adjusted Distance

*Notes: The figure reports the results of a regression of individual commuting distances on HOP, year-month-dummies and interactions of these variables (along with control variables). The outcome is work-home distances, calculated as driving distances between geographic centers of the municipality of the individual's place of residence and workplace. Place of residence is adjusted in the case that a person starts a new job during the year and the change of the place of living is observed in next January: then all previous months since the job start are corrected with the new address. 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. 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.*

## C Supplementary Figures




(a) By Occupation

(b) By Industry

Figure A.2: HOP and Distance at higher aggregation levels of occupations (first panel) or industries (second panel)

*Notes: Notes: The figure reports the average commuting distance and HOP for each 3-digit occupation (first panel) or 3-digit industry (second panel), between 2016-2019. Commuting distances are calculated as driving distances between geographic centers of the municipality of the individual's place of residence and workplace. The indicator for the WFH potential (HOP) is based on the working conditions that are reported in BERUFENET.*
*Source: 2 % random sample of the Integrated Employment Biographies (IEB) provided by the German Institute for Employment Research (IAB). BERUFENET. Own computations.*

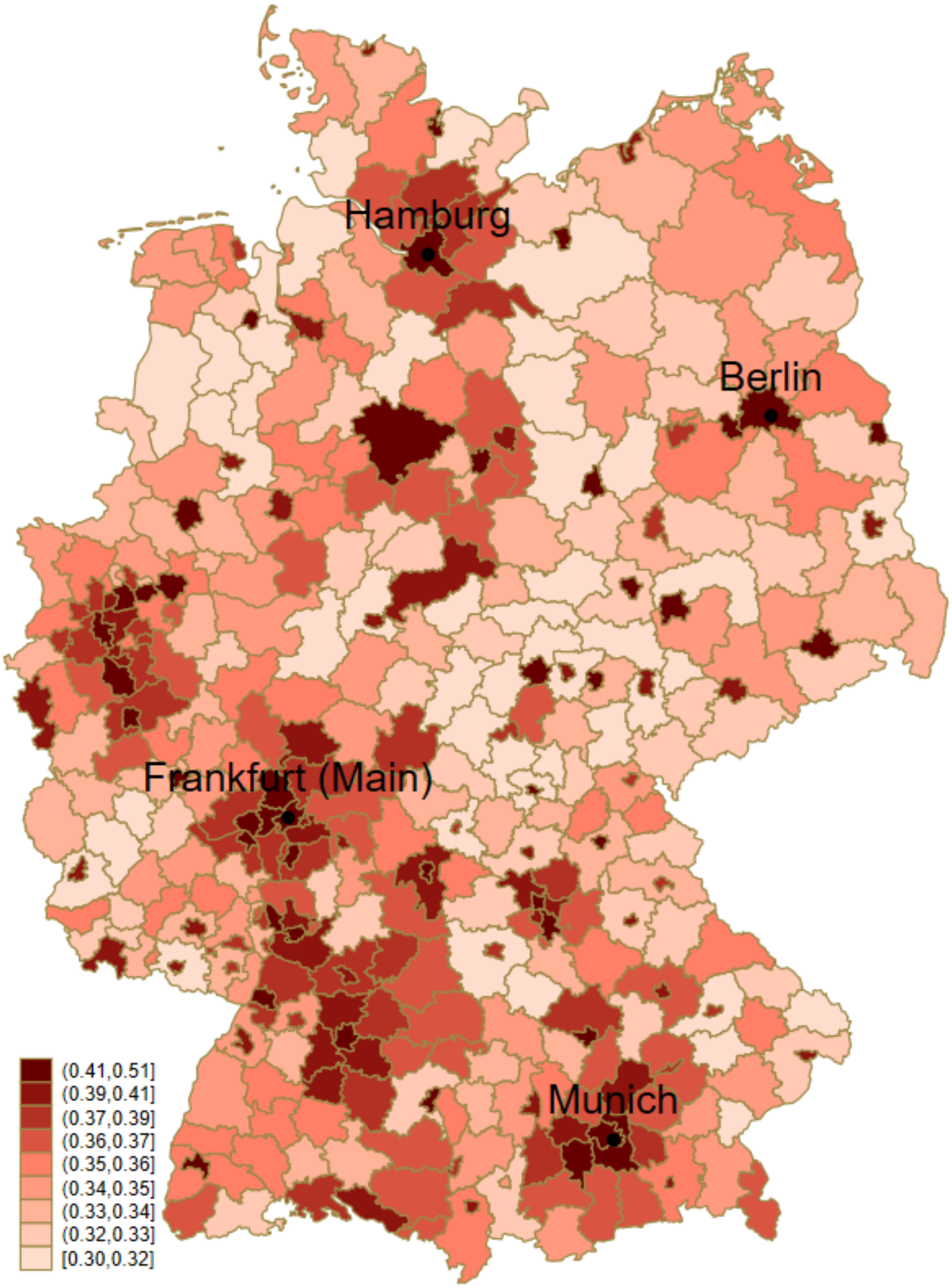



Figure A.3: Average HOP by region

*Notes: The indicator for the potential of working from (HOP) is based on the working conditions that are reported in BERUFENET. The map shows the average HOP of years 2016 to 2019 at the county level.*
*Source: BERUFENET. Own computations.*

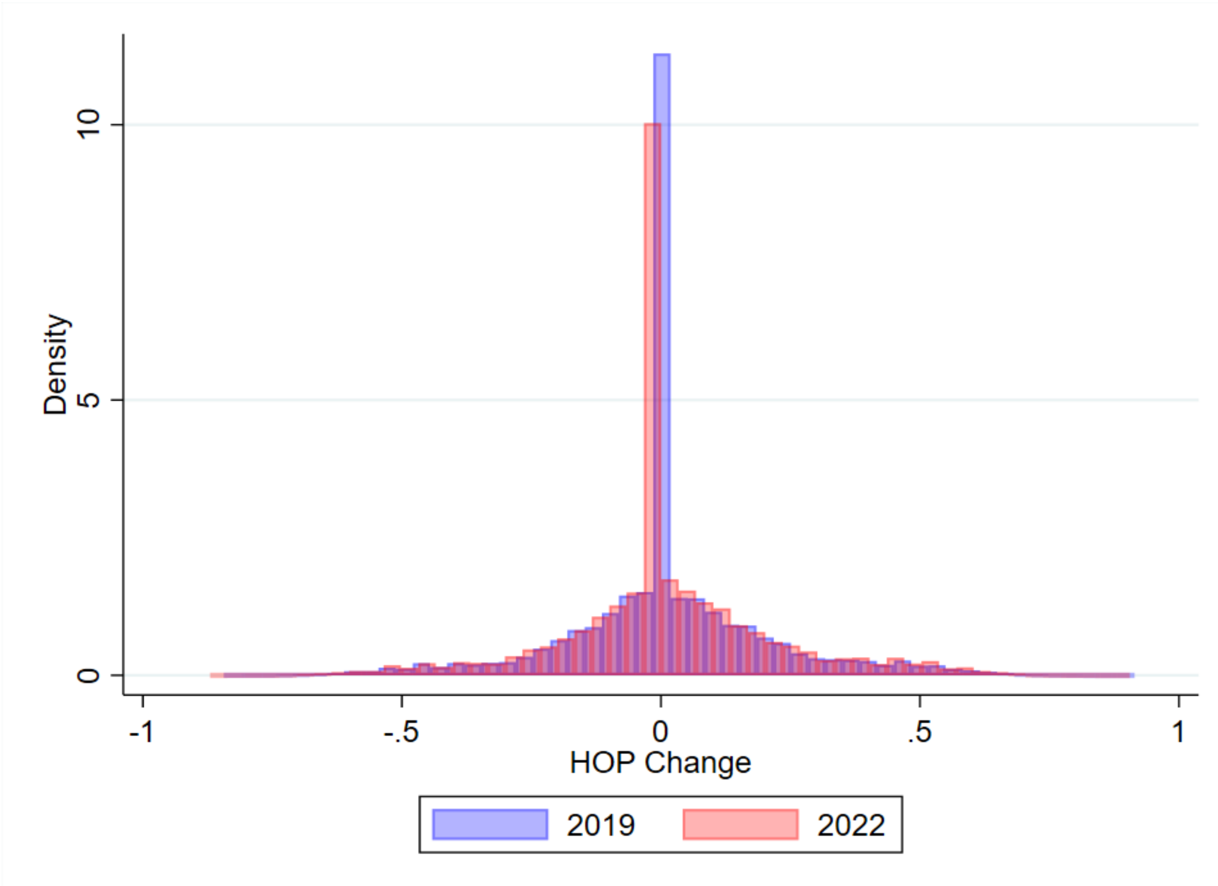



Figure A.4: HOP Change Distribution among Firm Changers

*Notes: The figure shows the distribution of changes in HOP for workers who changed between employers in 2019 and 2022. The indicator for the potential of working from (HOP) is based on the working conditions that are reported in BERUFENET*

*Source: 2 % random sample of the Integrated Employment Biographies (IEB) provided by the German Institute for Employment Research (IAB). BERUFENET. Own computations.*

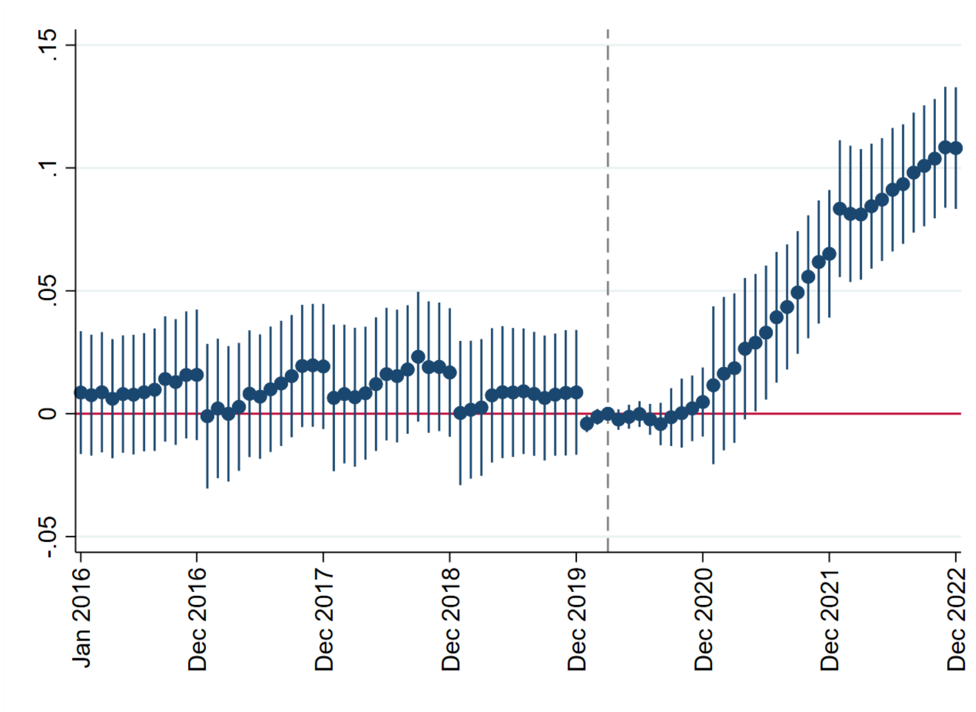



Figure A.5: Effect of HOP on Logarithmic Distance

*Notes: The figure reports the results of a regression of individual commuting distances on HOP, year-month-dummies and interactions of these variables (along with control variables). The outcome is work-home distances, calculated as logarithmic driving distances between geographic centers of the municipality of the individual's place of residence and 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. 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.*