



My home is my castle – The benefits of working from home during a pandemic crisis[☆]

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ABSTRACT

This paper studies the impact of working from home (WFH) on work relations and public health during the COVID-19 pandemic in Germany. Combining administrative data on SARS-CoV-2 infections and short-time work registrations, firm- and employee-level surveys and cell phone tracking data on mobility patterns, we find that WFH effectively shields employees from short-time work, firms from COVID-19 distress and substantially reduces infection risks. Counties with a higher share of teleworkable jobs experience fewer short-time work registrations and less SARS-CoV-2 cases. At the firm level, an exogenous increase in the take-up of WFH reduces the probability of filing for short-time work by up to 72 p.p. and the probability of being very negatively affected by the crisis by up to 75 p.p. Health benefits of WFH appeared mostly in the early stage of the pandemic and became smaller once tight confinement rules were implemented. This effect was driven by lower initial mobility levels in counties with more teleworkable jobs and a subsequent convergence in traffic levels once confinement was implemented. Our results imply that confinement and incentivizing WFH are substitutive policies to slow the spread of the coronavirus.

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1. Introduction

The global COVID-19 pandemic is the most severe health crisis since the Spanish flu, costing millions of lives worldwide. In addition to the public health calamity, the spread of the virus has caused a harsh economic downturn. Most economists agree that, in the medium term, there is little trade-off between fighting the

pandemic and stabilizing the economy (Kaplan et al., 2020): mitigating the economic impact of COVID-19 requires to curb the pandemic because individuals' behavioral responses to a large-scale outbreak have severe economic consequences. While voluntary behavioral changes can play an important role in reducing infections, these are generally too small and occur too late, as individuals do not fully take into account the infection externalities they have on others (Jones et al., 2020). Government-mandated behavioral changes via non-pharmaceutical interventions (NPIs) are thus necessary in order to keep the virus at bay (Eichenbaum et al., 2020). The short-run costs and benefits of different NPIs may vary substantially though: while strict lockdowns with mandated stay-at-home-orders and business closures are considered to be the most effective NPI to fight the pandemic (Flaxman et al., 2020), they are economically extremely costly (Fadinger and Schymik, 2020). By contrast, other NPIs that aim at reducing social interac-

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tions usually have a more moderate impact on infections and the economy (Brotherhood et al., 2020).

In this paper, we study the impact of one specific NPI: working from home (WFH, telework). Using data for Germany, we show that WFH is an effective measure to simultaneously maintain economic activity and mitigate the spread of SARS-CoV-2.¹ To quantify the economic and epidemiological effects of WFH, we compute an index of WFH potential, drawing on a pre-crisis employment survey. We collapse individual-level information about the teleworkability of respondents' jobs to the occupational level and combine the resulting shares with administrative data on the occupational composition of all 401 German counties.²

First, we investigate the impact of WFH on economic activity during the spring 2020 wave of the COVID-19 pandemic. The main instrument used to deal with the labor-market impact of the pandemic in Germany was the federal short-time work scheme (*Kurzarbeit*), which was substantially expanded in March 2020 and provided wage subsidies of around two-thirds of foregone earnings to companies in "inevitable" economic distress during the year 2020.³ While unemployment hardly increased in Germany in spring 2020, firms filed short-time work (STW) applications for around 30 percent of the labor force.⁴ Using administrative data and firm-level survey information, we show that regions and firms with a higher WFH potential experienced significantly fewer applications for STW.⁵ A 1 p.p. increase in the share of teleworkable jobs at the county level reduces STW applications relative to total employment by between 0.8 and 2.6 p.p. At the firm level, we use industry-specific WFH potential as an instrumental variable for the actual take-up of telework in April 2020 to provide causal evidence for the employment- and output-preserving effect of telework. Firms that intensified telework during the crisis were 49 to 72 p.p. less likely to file for short-time work and up to 75 p.p. less likely to report adverse effects of the COVID-19 crisis. Overall, our results imply that telework helped strongly to mitigate the short-run negative effects of supply-side restrictions imposed by confinement rules on firms and workers. This is consistent with evidence for the US: Papanikolaou and Schmidt (2020) find that US industries with higher WFH potential experienced smaller declines in employment in spring 2020, while Koren and Peto (2020) show that US businesses that require face-to-face communication or close physical proximity were particularly vulnerable to confinement.

Second, we study the effect of WFH on SARS-CoV-2 infections before and after confinement rules were imposed in Germany. While the first cases of SARS-CoV-2 in Germany were recorded in late January, the pandemic really gained momentum in early March when people returned from skiing holidays in Austria (Felbermayr et al., 2020). In the meantime, authorities gradually ratcheted up restrictions on public life.⁶ On March 22, all German

states imposed strict lockdown measures in a coordinated manner.⁷ We exploit detailed weekly panel data on SARS-CoV-2 infections and deaths during the first wave of the pandemic from its outbreak until the end of the confinement (January 29 until May 06, 2020) for all 401 counties. Using cross-sectional variation, we find that a 1 p.p. increase in the share of teleworkable jobs is associated with a 4.5 to 8.1 percent reduction in the infection rate. Exploiting temporal variation within counties, we show that the infection-reducing effect of WFH was larger in the first weeks of the pandemic and faded after the implementation of lockdown measures.⁸ This finding is in line with modeling studies from the epidemiological literature (Koo et al., 2020), which suggest that WFH is more effective in containing the virus at low levels of infections. Additionally, we use mobility data collected from a large German mobile phone provider to show that our results are consistent with mobility patterns. The level of work-related trips was systematically lower in high-WFH-ability regions before confinement but this differential in mobility disappeared once the lockdown was in place and most people stayed at home. Overall, our results imply that WFH and lockdowns are to some extent substitutable policies. This has important implications for the reactivation period of the economy: to keep infection rates low while maximizing the level of economic activity, WFH should be a policy prescription as long as infection risks remain present.⁹

An arguable limitation of our study is that we primarily exploit cross-sectional variation in WFH opportunities instead of (quasi-) random variation in actual WFH take-up during the crisis. We address potential threats to validity in several ways: First, by employing WFH measures that proxy for WFH *feasibility* we reduce the risk that our estimates are confounded by other behavioral responses during the crisis that may be interdependent with *actual* WFH. In other words, we estimate the effect of the intention to treat rather than the treatment effect. Second, we account for a large set of potential confounding factors. In our regional analysis these include differences in population density, local economic conditions, regional healthcare capacities, morbidity of the local population, and differences in social capital. Third, we corroborate our regional analysis with firm-level and industry-level data. Fourth, we also exploit time variation in short-time work and infections within counties using difference-in-differences estimators. Finally, we show that our results are robust to a battery of sensitivity checks reported in the Appendix.

Our study builds on the recent contributions quantifying the potential of jobs for telework. Dingel and Neiman (2020) determine the teleworkability of occupations by assessing the importance of workers' presence at the workplace using task information. Instead, we draw on the approach of Alipour et al. (2020), who rely on an administrative employee survey that directly reports on workers' home-working practices before the COVID-19 outbreak and their own assessments of home-working opportunities to construct measures of WFH potential. In sensitivity checks we show that our results are robust to using Dingel and Neiman's task-based measure.¹⁰

Furthermore, we contribute to the literature studying the costs and benefits of WFH by socio-economic status (SES). According to our survey, a key individual characteristic associated with having a job with high WFH potential is having a university degree. In line with this finding, Mongey et al. (2020) show that US workers with

¹ Compared to other NPIs, an important feature of WFH is the alignment of private and public incentives: WFH allows individuals to work efficiently, to preserve their jobs, and at the same time to reduce infection risks. By contrast, individuals may be reluctant to respect a government-imposed lockdown because of the associated economic costs that may outweigh personal health benefits. This makes it much easier to achieve a high level of compliance for WFH orders than for other NPIs, even in the absence of strict monitoring.

² This strategy is akin to Bartik (1991) and Blanchard and Katz (1992), who exploit exogenous variation in regional economic structure to assess labor-market impacts of economic shocks.

³ In September 2020, the duration of the scheme was extended into 2021.

⁴ This contrasts with the US, where due to the absence of a comprehensive furloughing scheme, the pandemic led to a steep increase in unemployment claims (Forsythe et al., 2020).

⁵ By contrast, Kong and Prinz (2020), find no impact of stay-at-home orders on unemployment claims using high-frequency data for the US.

⁶ See Weber (2020) and Appendix A.2 (Adams-Prassl et al., 2020b; Franzen and Botzen, 2011; Ganyani et al., 2020; Hall et al., 2020; Held et al., 2005; Meyer et al., 2017; Yassenov, 2020) for details on the confinement measures in Germany.

⁷ Exceptions were Bavaria and Saxony, which started confinement already a day earlier.

⁸ Exploiting within-county variation, we find an around 2 to 5 percent larger reduction of infection rates before the confinement on average.

⁹ In line with this prescription, Kucharski et al. (2020) find strong complementarities between WFH and contact tracing in reducing effective reproduction numbers based on a modeling study.

¹⁰ Other survey-based WFH studies are, for example, Papanikolaou and Schmidt (2020) or Von Gaudecker et al. (2020).

low WFH potential are less educated, have lower income and fewer liquid assets. Using real-time survey data, Adams-Prassl et al. (2020) document a negative correlation between US and UK workers' self-reported share of teleworkable tasks and the probability of job loss during the COVID-19 pandemic. We complement their findings by showing a causal effect of WFH on reducing firms' short-time work applications. In this respect, WFH tends to exacerbate economic inequality during the pandemic. However, we also provide evidence for positive economic spillover effects of WFH: a one-percent increase in WFH potential is associated with a more than proportionate reduction in the probability of short-time work. Thus, when some employees start working from home, also jobs without WFH opportunity are preserved.

The association between SES and health is well documented: High-SES individuals tend to live longer, even though the precise channels of this finding remain unclear (Chetty et al., 2016; Stringhini et al., 2017). In the context of the COVID-19 pandemic, the correlation between a job's WFH potential and the individuals' SES is a specific mechanism contributing to this outcome: a larger WFH potential is associated with significantly less regional SARS-CoV-2 infections and deaths. This mostly benefits high-SES individuals, who can work from home and stay healthy. We also find that the impact of regional WFH potential on infections is stronger in high-income regions. This is in line with Chang et al. (2020), who find smaller reductions in mobility and, correspondingly, more SARS-CoV2 infections in low-income neighborhoods of US cities.¹¹ However, there are also indirect health benefits of higher regional WFH potential to workers who cannot engage in telework: lower contact rates while commuting and at the workplace also reduce the infection risk of workers who cannot work remotely.

Finally, we contribute to the literature investigating the impact of pandemic-related labor supply shocks. Karlsson et al. (2014) study the impact of the Spanish flu on economic outcomes in Sweden. Duarte et al. (2017) estimate the effect of work absence due to the 2009 flu pandemic on labor productivity in Chile.

In the next section, we examine the impact of WFH on regional and firm-level short-time work filings and firm distress. In Sections 3 and 4, we look at the relationship between WFH and SARS-CoV-2 infections at the county level, both before and after confinement, and study regional variation in mobility patterns during the first wave of the COVID-19 pandemic. Finally, Section 5 concludes.

2. Working from home and labor market adjustments in Germany during the COVID-19 crisis

2.1. Measuring working from home in Germany

To measure the geographical distribution of jobs that can be performed at home, we follow Alipour et al. (2020) and combine representative employee-level information from the 2018 BIBB/BAuA Employment Survey with regional employment counts from the Federal Employment Agency. Specifically, we first aggregate individual-level information on WFH to the occupational level and use information on the composition of occupations in all 401 counties to further aggregate occupation-specific WFH shares to the county level. Thus, by construction, regional differences in WFH potential are determined by county-level variation in the occupational composition.

We compute three measures of WFH feasibility: First, the share of employees in a county who work from home "always" or "frequently" (*WFH freq*). Second, the share of employees working at home at least occasionally (*WFH occ*). And third, the share of

employees who have ever worked from home or who do not exclude the possibility of home-based work, provided the company grants the option (*WFH feas*). The last measure hence identifies jobs which can (at least partly) be done from home, independently of workers' previous teleworking experience. Consequently, we interpret *WFH feas* as an upper bound for the share of employees who may work from home during the crisis. As switching to telework during the pandemic is arguably associated with transition costs, we conjecture that frequent and occasional teleworkers will be able to use telework earlier and to a greater extent than employees who have no previous teleworking experience. We therefore interpret *WFH freq* as a lower-bound estimate for the share of employees actually working from home during the pandemic.

In the aggregate, before the pandemic, about 9 percent of employees worked from home on a regular basis, 26 percent did so at least occasionally, and 56 percent have jobs which in principle can be partly or completely performed at home. At the worker level, differences in WFH potential are mainly attributable to different task requirements of teleworkable and non-teleworkable jobs. Jobs that can be done from home are typically distinguished by a high content of cognitive, non-manual tasks, such as working with a computer, researching, developing and gathering information (Alipour et al., 2020; Mergener, 2020).¹² Details on the variable construction and descriptive statistics are reported in Appendix A.1.

2.2. Working from home and short-time work: regional evidence

To contain the spread of the Coronavirus, the German government enforced drastic containment measures. Restrictions were gradually tightened starting in February 2020, and from March 22 to May 6 a strict lockdown was imposed (see Appendix A.2 for details). Many companies, especially in the hospitality, food services and retail sector were subjected to mandatory shutdowns. Survey evidence suggests that during this period nearly 40 percent of the workforce switched to telework to reduce infection risk (Eurofound, 2020). The consequences of the economic shock are reflected in the large number of filings for short-time work allowances. The federal STW scheme (*Kurzarbeit*) was substantially expanded in March 2020 until the end of the year.¹³ It is normally used during heavy recessions and enables companies in "inevitable" economic distress to cut labor costs by temporarily reducing their employees' regular working hours by up to 100 percent instead of laying them off. Up to 67 percent of employees' foregone earnings are subsequently compensated by the Federal Employment Agency through the unemployment insurance fund.¹⁴ In March and April 2020, STW applications for 10.7 million workers were filed, corresponding to 31 percent of total employment in September 2019. Note that in Germany short-run labor market adjustments to the COVID-19 shock occurred primarily in terms of STW expansions and only very little happened via an increase in unemployment. In contrast to the unemployment surge in the US (see Coibion et al., 2020), the net number of unemployed in Germany increased by less than 250,000 in March and April 2020.¹⁵

In this section, we assess whether the possibility to work from home mitigates the COVID-19 shock by increasing the likelihood that workers can continue to perform their job instead of being

¹¹ Glaeser et al. (2020) – drawing on data for 5 US cities – show that higher mobility is associated with more SARS-CoV-2 infections.

¹² In Appendix A.3 we discuss correlations between employee characteristics and our WFH measures. Most of the variation in WFH across individuals is explained by occupational differences, while the skill level remains very significant even when accounting for workplace and demographic characteristics.

¹³ In September 2020 it was extended until end of 2021.

¹⁴ Previous research indicates that STW schemes can be very effective in retaining employment and avoiding mass layoff during economic crises (see e.g. Balleer et al. (2016), Cooper et al. (2017), Boeri and Bruecker (2011)).

¹⁵ In comparison, this number reached 3.3 million during the Great Recession in 2008/2009 (Bundesagentur für Arbeit, 2020).

put on short-time work. We examine this relationship by estimating the impact of WFH on STW applications at the regional level. To this end, we source administrative records on STW applications in March and April 2020 from the Federal Employment Agency. In Section 2.3, we provide corroborating evidence on the relationship between WFH and STW using firm-level data.

When interpreting the relationship between WFH and STW during the pandemic, one may be concerned about endogeneity for two reasons. First, regions with higher infection rates are likely to experience more STW applications, as a higher fraction of firms are forced to shut down, and more WFH because of greater safety concerns. We cannot directly control for differences in infection rates, however, as this would provoke a “bad control bias”: WFH is likely to have a causal impact on both STW and local infection rates. We instead account for other county characteristics which determine the regional spread of SARS-CoV-2, such as infections in neighboring regions, the local age structure, population density, population health, healthcare infrastructure and factors that have been shown to proxy for people’s disposition to comply with public containment measures, among others. Second, there may be omitted regional characteristics that are correlated with the fraction of teleworkable jobs and also affect short-time work applications.

We thus account for a wide range of potential confounding factors at the county level. We will use the same sets of covariates in the regional infection analysis in the following Section 3. The first set of covariates comprise our *Baseline* controls, which we include in all specifications. Baseline controls include the number of days since the first detected infection, to account for the non-linear dynamics of the pandemic. To deal with transmission of infections from neighboring counties, we control for spatially weighted infection rates. These are defined as the log-weighted mean of infection rates in other counties, using inverse distances as weights. To account for differences in the density of human activity, baseline controls also include region-specific settled area, population and GDP (all in logs). Second, we include a set of *Economy* controls to account for more detailed regional differences in economic activity beyond GDP, including the fraction of (in- and outward) commuters in the local workforce, an infrastructure index that captures reachability of airports, the fraction of households with broadband internet access (≥ 50 Mbps), the fraction of low-income households in the county ($\leq$ EUR 1,500 per month) and the employment shares in the aggregate services, manufacturing and wholesale/retail sectors. Third, we include *Health* covariates to account for regional differences in healthcare capacity and the morbidity of the local population. Health covariates include the fraction of male population, the fractions of population in working age (15–64 yrs.) and elderly (≥ 65 yrs.), remaining life expectancy at age 60, the pre-crisis death rate, the number of intensive-care-unit beds per 100,000 inhabitants and the number of hospitals per 100,000 inhabitants. Lastly, we account for differences in social capital, which have been shown to explain varying degrees of compliance with social distancing behavior and containment measures (Barrios et al., 2021; Borgonovi and Andrieu, 2020). Our *Social Capital* controls include crime rates, voter turnout and vote shares of populist parties in the 2017 federal election and the number of registered non-profit associations per 100,000 inhabitants. Summary statistics and variable sources are reported in Appendix A.1.

Table 1 reports the OLS results from estimating the regional percentage share of employees for which STW was filed in March and April 2020 as a function of regional WFH potential and controls. The Table is divided into three panels, one for each of our WFH measures. Regressions are weighted with pre-pandemic employment to give more importance to larger counties. This allows us to recover the conditional mean association between STW applications and telework at the individual level. Columns

(1) to (5) report the OLS coefficients controlling for the different subsets of controls. Column (5) includes the full set of covariates.

The relationship between local WFH potential and STW applications is negative and significant at the one-percent level for all three WFH measures and across all specifications. The estimates for *WFH feas* are consistently smaller than for *WFH occ* and *WFH freq*. This is in line with our interpretation that the measures reflect the upper and lower bounds of a county’s actual WFH capacity, respectively. The estimates in Column (5) suggest that a 1 p.p. increase in local WFH capacity reduces the share of STW applications by 0.84 to 2.6 p.p. Increasing WFH by one standard deviation thus is associated with a 3.5 to 4.4 p.p. decrease in the local fraction of jobs registered for STW. A coefficient above one points to spillover effects from telework: to the extent that WFH allows firms to maintain business operations during the crisis, employees who continue to work on the company premises also benefit by experiencing a lower risk of STW.¹⁶ Overall, the results strongly support the employment-preserving effect of WFH during the crisis.

Section A.4 in the Appendix discusses several robustness checks. First, we show that using realized STW instead of STW applications gives very similar results. We also perform a placebo test and show that in January 2020 (the month before the COVID-19 crisis started) there was no statistically significant relation between WFH and STW. Finally, we use a difference-in-differences estimator to confirm that WFH reduced STW applications only during the pandemic. Section A.8 corroborates the regional analysis with estimations exploiting industry-level variation. We also show that our results are robust to using Dingel and Neiman (2020)’s task-based WFH feasibility index instead of our survey-based measures.

2.3. Working from home, short-time work and COVID-19 distress: firm-level evidence

Next, we move to the firm level to assess whether WFH had a mitigating effect on the economic shock of the COVID-19 pandemic. We draw on the ifo Business Survey, a representative survey of German firms, which elicits information on business expectations and conditions as well as various company parameters on a monthly basis.¹⁷ In April 2020 roughly 6,000 firms were questioned about the business impact of and the managerial responses to the pandemic. Among a list of non-exclusive mitigation measures, the most frequently mentioned response was the intensified use of telework. Overall, nearly two-thirds of the companies stated greater reliance on telework as part of their strategy to cope with the crisis. Almost half of the surveyed companies filed for STW and 30 percent report a “very negative” impact of the pandemic on their business. In the following, we use these two indicators as our main outcome measures of the economic impact of the crisis on firms.

The firm-level analysis allows us to address several endogeneity concerns regarding the WFH estimates. In particular, there may be factors that simultaneously affect firms’ disposition to use STW and WFH in their efforts to cope with the crisis. For instance, idiosyncratic infection risk might increase the likelihood of employing both STW and telework, leading us to underestimate the mitigating effect of WFH in an OLS regression. Mandatory business closures, on the other hand, are likely to increase the propensity of STW while reducing the likelihood of telework. Demand-side shocks may also be correlated with both STW and WFH and cause bias. We account for these potential confounding factors by controlling for observable covariates and by using our measure

¹⁶ Our analyses of the epidemiological effects in Section 3 suggest that these employees equally experience a lower exposure to infection risk.

¹⁷ See Link (2020), Buchheim et al. (2020) and Sauer and Wohlrabe (2020) for a more detailed description of the survey.

Table 1
The Effect of Working from Home on Short-Time Work Applications across Counties.

	(1)	(2)	(3)	(4)	(5)
<i>WFH feas</i>	−1.22*** (0.22)	−0.70*** (0.21)	−1.28*** (0.23)	−1.24*** (0.25)	−0.84*** (0.24)
<i>R</i> ²	0.23	0.33	0.27	0.28	0.36
NUTS-3 regions	401	399	391	401	389
<i>WFH occ</i>	−1.70*** (0.24)	−1.15*** (0.23)	−1.81*** (0.25)	−1.88*** (0.27)	−1.46*** (0.29)
<i>R</i> ²	0.27	0.35	0.30	0.31	0.38
NUTS-3 regions	401	399	391	401	389
<i>WFH freq</i>	−3.34*** (0.50)	−2.20*** (0.51)	−3.48*** (0.54)	−3.69*** (0.60)	−2.60*** (0.65)
<i>R</i> ²	0.27	0.34	0.29	0.29	0.37
NUTS-3 regions	401	399	391	401	389
Set of Controls					
Baseline	×	×	×	×	×
Economy		×			×
Health			×		×
Social Capital				×	×

Notes: Dependent variable is the percentage of the total number of persons mentioned in short-time work applications in March and April 2020 relative to employment in June 2019 based on data from the Federal Employment Agency. *WFH* is the percentage share of employees in the county with jobs that are suitable for telework (*WFH feas*) or who either at least occasionally (*WFH occ*) or frequently (*WFH freq*) worked from home in 2018. Observations correspond to NUTS-3 regions (counties) and estimates are weighted based on employment as of June 2019. *Baseline* controls include region-specific log population, log settled area, region-specific log GDP, the number of days since the first infection and log spatial infection rates (defined as a weighted mean of infection rates in other counties using inverse distances as weights) as of April 30th. *Economy* controls include the fraction of (in- and outward) commuters in the local workforce, an infrastructure index that captures reachability of airports, the fraction of households with broadband internet access (≥ 50 Mbps), the fraction of low-income households ($\leq$ EUR 1,500 per month), the share of workers employed in services, manufacturing, and wholesale/retail sectors, respectively. *Health* controls include the fraction of male population, the fractions of population in working age (15–64 yrs.) and elderly (≥ 65 yrs.), the expected remaining lifetime of people with age 60, the death rate, intensive-care-unit beds per 100,000 inhabitants and hospitals per 100,000 inhabitants. *Social Capital* controls include crime rates, voter turnout, vote shares of populist parties and the number of all registered associations per capita. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

of industry-level WFH potential, which is plausibly orthogonal to firms' idiosyncratic COVID-19 shocks, as an instrument for intensified telework usage. Since firms expanded WFH both at the intensive and the extensive margin, we use *WFH feas*, which measures the overall share of teleworking jobs in a given industry, as our preferred instrument and estimate the following 2SLS specification:

$$y_{isc} = \beta_0 + \beta_1 \times \text{telework}_{isc} + \delta'X_{isc} + \alpha_c + \varepsilon_{isc} \quad (1)$$

$$\text{telework}_{isc} = \pi_0 + \pi_1 \times \text{WFHfeas}_s + \lambda'X_{isc} + \alpha_c + v_{isc}, \quad (2)$$

where y_{isc} is either a dummy variable that indicates if firm i of industry s located in county c applied for STW or if the firm reports a very negative impact of the pandemic on business. Our variable of interest telework_{isc} is a dummy indicator for firms who increased telework in April 2020. The regressions also include county fixed effects (α_c) and a set of control variables (X_{isc}). The baseline controls include firm size, firms' export share, survey fixed effects and fixed effects for the survey completion date. Additional controls include self-reported business conditions and business expectations in Q4 2019 as well as an indicator for firms operating in an industry subject to mandatory business closure in April 2020.¹⁸ In our sample, nearly 16 percent of businesses were affected by mandatory closures or severe restrictions.¹⁹ In Table A11 in Appendix A.5, we report results with demand controls by including the leave-one-out 2-digit industry average of firms reporting a drop in demand due to the COVID-19 crisis. We do not include the demand control in the

¹⁸ Business conditions (expectations) are elicited on a trichotomous scale including negative (more unfavorable), neutral (roughly the same), and positive (more favorable).

¹⁹ Mandatory closures of non-essential businesses and institutions were introduced by the end of March 2020 and were gradually lifted from April 19, onward. The shutdown affected primarily restaurants (only pick-up and delivery services allowed), retail stores, close-proximity services (e.g., barber shops), hotels and cultural institutions (e.g., museums, night clubs).

main table as the information is only available for a reduced sample of firms. Summary statistics of the firm-level variables are reported in Appendix Table A3.

Table 2 reports the results for our two outcomes, STW applications (Panel A) and COVID-19 distress (Panel B). We report the reduced-form (Columns 1 and 2), OLS (Columns 3 and 4) and IV (Columns 5 and 6) regression results and the first-stage coefficient $\hat{\pi}_1$.²⁰ Odd columns include baseline controls only, even columns add our additional controls. Standard errors are clustered at the 2-digit industry level. Our instrument *WFH feas* is negatively correlated with both outcomes and significant at the one-percent level. The first-stage Kleibergen-Paap Wald F statistics are above 50, implying that the instrument is strong. The OLS estimates indicate that reliance on telework is associated with a statistically significant decrease in the likelihood of filing for STW (reporting an adverse COVID-19 shock) by 12.4 (14.7) p.p.; these estimates are reduced to 5.4 (6.5) once we include all covariates. Furthermore, firms reporting a weaker state of business before the pandemic are also more likely to file for STW and report a particularly negative impact of the crisis. Unsurprisingly, the outcomes for firms that were subject to mandatory business closures appear also significantly worse.

Columns (5) and (6) show that the IV estimates are negative and significant at the one-percent level: relying on telework reduces the firm-level probability to file for STW (report an adverse COVID-19 impact) by 49.2 (39.9) p.p. when accounting for all covariates. Notice that controlling for mandatory business shutdowns in Column (6) reduces the magnitude of the IV estimate considerably compared to Column (5). As closures were specifically mandated in industries characterized by high degrees of physical proximity among workers and customers and low teleworking potential (e.g., food services, retail trade, personal services), accounting for this variable is important for the reliability of the IV strategy. The IV estimates are

²⁰ Table A.10 in Appendix A.5 reports the full first-stage regressions.

Table 2
Effect of Working from Home on Severity of COVID-19 Crisis – Firm-Level Evidence.

	RF		OLS		IV	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>Panel A: Participated in Short-Time Work Scheme</i>						
Intensified Telework			–12.41*** (4.00)	–5.40*** (1.99)	–71.55*** (11.34)	–49.42*** (13.80)
WFH feás	–0.81*** (0.20)	–0.45*** (0.12)				
Mandatory Shutdown		29.58*** (5.68)		34.58*** (6.00)		20.64*** (6.46)
State of Business 2019Q4						
negative		11.98*** (1.74)		12.08*** (1.81)		10.69*** (1.91)
positive		–9.92*** (1.71)		–10.39*** (1.79)		–9.77*** (1.72)
R ²	0.15	0.20	0.13	0.20		
Firms	6028	5796	6028	5796	6028	5796
First stage estimate (×100)					1.14***	0.92***
First stage KP F-stat					50.88	80.26
<i>Panel B: Negative Corona Shock</i>						
Intensified Telework			–14.74*** (5.04)	–6.57** (2.54)	–74.72*** (14.80)	–39.13*** (13.84)
WFH feás	–0.86*** (0.26)	–0.37*** (0.12)				
Mandatory Shutdown		40.58*** (7.18)		43.93*** (7.60)		33.94*** (6.40)
State of Business 2019Q4						
negative		11.01*** (2.66)		11.00*** (2.77)		9.86*** (2.98)
positive		–9.16*** (1.99)		–9.56*** (2.00)		–9.34*** (1.89)
R ²	0.17	0.26	0.15	0.25		
Firms	5363	5156	5363	5156	5363	5156
First stage estimate (×100)					1.15***	0.94***
First stage KP F-stat					52.87	80.88
Baseline	×	×	×	×	×	×
Controls		×		×		×

Notes: The dependent variable is an indicator (rescaled by 100) identifying firms who participated in the short-time work scheme (Panel A) or who report a “very negative” impact of the COVID-19 crisis in April 2020 (Panel B). *Intensified telework* is a binary variable identifying firms who report an intensified usage of telework in response to the COVID-19 crisis. Baseline controls (not reported) include firm size in terms of employment (5 size categories), the share of sales generated abroad, fixed effects for the date of survey completion, survey fixed effects (Construction, Wholesale/Retail, Service and Manufacturing) and location fixed effects at the county level. Additional controls include a dummy for firms operating in an industry subject to mandatory business closures, pre-crisis business conditions in Q4 2019 (baseline: neutral) and business expectations in Q4 2019 (3 categories, not reported). Data are from the ifo Business Survey. Standard errors clustered at the 2-digit NACE level reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

substantially larger than the OLS estimates. A plausible explanation is that OLS estimates are biased towards zero due to unobserved idiosyncratic shocks. For instance, a confirmed COVID-19 case in the company is likely to prompt an immediate managerial response by mandating telework and putting a fraction of the workforce on STW. Furthermore, we measure WFH very coarsely at the firm level without accounting for different teleworking intensities. Thus, IV estimates also adjust for attenuation bias due to measurement error in the explanatory variable. In [Appendix A.5](#), we replicate the estimations on our reduced sample, additionally controlling for the pandemic-induced demandshock. The likelihood of filing for STW and reporting an adverse effect of the crisis increases significantly when demand contracts. The WFH coefficient estimates remain statistically significant and their magnitude does not change substantially. Overall, the firm-level results corroborate the evidence from the regional analysis, showing that WFH has been effective in mitigating the COVID-19 shock.

3. Working from home and the spread of SARS-CoV-2 across German counties

We now turn to the impact of WFH on SARS-CoV-2 infections. WFH is expected to reduce infections for the following reasons. A higher county-level WFH share reduces the fraction of workers

working at the business premises. This directly lowers the contact rate – defined as the average number of contacts of an infected individual, which is a key parameter in infectious disease models ([Giesecke, 2002](#)) – by reducing the number of personal contacts both at work and while commuting. In addition, a larger share of workers engaging in telework also allows co-workers who have to work on site to keep more physical distance. We first study the effectiveness of WFH in reducing SARS-CoV-2 infections using cross-sectional variation before exploiting time variation within counties in Section 4.

To measure SARS-CoV-2 infections and fatality cases in Germany, we use administrative data provided by the Robert-Koch-Institut (RKI). To minimize measurement issues caused by reporting lags over weekends, we consider weekly data measured on Wednesdays. Our final dataset covers 15 weeks of the pandemic from week 1 (January 23–29, 2020) to week 15 (April 30 – May 06, 2020). The sample covers the beginning of the pandemic in Germany and ends with the lifting of confinement after the first wave of the pandemic.²¹

To explore the cross-sectional association between regional variation in telework and the spread of COVID-19 across counties,

²¹ See [Appendix A.1](#) for a more detailed description and summary statistics of the RKI data.

we regress the (log of) regional SARS-CoV-2 infection rates, defined as the cumulative number of cases relative to the number of inhabitants, on our regional WFH measures, using disease data from the last sample week (Wednesday, May 06, 2020).²² In all specifications we weight observations according to their population. Equivalently to the county-level results on STW in the previous Section 2, we use our four distinct groups of covariates. All specifications include the set of *Baseline* covariates. Furthermore, we alternately include the *Economy*, *Health* and *Social Capital* covariates. The most stringent specification includes the full set of controls.

Table 3 reports the estimation results. We find a robust negative association between WFH and infection rates across German counties throughout all specifications and WFH proxies. Our estimated coefficient of interest is significant at the one-percent level for all WFH measures when including baseline controls in Column (1). Quantitatively, an increase in the WFH suitability (*WFH feas*) by 1 p.p. is associated with a 4.5 percent decrease in the local infection rate. An equivalent increase in *WFH freq* is associated with a 12 percent reduction of the infection rate. Consider the following thought experiment to illustrate the quantitative implication of the estimates: If Berlin, a county with a rather high share of *WFH freq* jobs (11.72 percent) had a one-standard-deviation lower share of such jobs, corresponding roughly to numbers for the county Bayreuth (Bavaria), this would imply 940 additional cases on top of the actual 5,992 cases that have been reported in Berlin as of May 06, 2020.

Note that we do not observe the actual fraction of workers engaging in telework during the sample period. Instead, our WFH measures are proxies for this number. If there are adjustment costs for workers switching to telework due to COVID-19, *WFH freq* is plausibly most closely correlated with the actual fraction of workers working from home. We also observe the coefficient magnitudes of *WFH freq* to be larger compared to using *WFH occ* which itself yields larger coefficient estimates than *WFH feas*. Importantly, because all three measures of telework are constructed with data that was collected before the COVID-19 crisis, the estimates are not subject to reverse causality. Instead, the coefficients on the WFH measures can be interpreted as reduced-form estimates, whose magnitude is plausibly downward biased relative to the true one due to mis-measurement.

When we add economy covariates in Column (2), the magnitude of the WFH coefficients decreases slightly but remains significant at the one-percent level for *WFH feas* and *WFH occ* and at the ten-percent level for *WFH freq*. In Column (3) we use the set of health covariates instead and obtain very similar results compared to the baseline estimates from Column (1). Controlling for regional differences in social capital renders our WFH coefficients slightly larger compared to the baseline estimates and significant at the one-percent level.²³ Lastly, we include the full set of controls in Column (5). The coefficients of interest remain significant at the one-percent level for *WFH feas* and *WFH occ* and significant at the ten-percent level for *WFH freq*.

We further assess the robustness and plausibility of the infection-reducing effect of WFH in Appendix A.6. Since systematic measurement error caused by regional variation in testing capacities might play a role in observing different infection rates, we show that our results are robust to considering fatality rates instead. We also show the robustness of the results in Table 3 based on a Poisson estimator, using either the number of infections or deaths as outcome variables to account for zero or few cases in

some counties. To further assess whether the negative regional correlation between WFH and coronavirus infections indeed captures reduced workplace-related contagions, we interact WFH with regional working-age-population or employment shares. WFH shares indeed have a stronger impact on SARS-CoV-2 infections in regions where a larger fraction of the population is in the labor force. In line with the literature studying costs and benefits of WFH by SES (e.g. Chang et al., 2020), we also find health benefits of WFH to be larger in more affluent counties. We also replicate our results using infection data from other weeks. Lastly, we study regional spillover effects of WFH in addition to the within-county effects stressed above. Our evidence suggests that commuting spillovers are indeed important for commuting-intensive counties in both, counties where many commuters have their workplace, and counties where commuters reside.

4. Working from home and SARS-CoV-2 infections over time

In this section we further investigate how WFH affects the spread of COVID-19 using time variation within counties. A central policy question with regard to confinement strategies is whether WFH has a complementary or a substitutive effect with respect to confinement. In other words, we ask if counties where more jobs are suitable for telework have lower infection rates because confinement can be implemented more effectively or if WFH instead allows for more social distancing even in the absence of confinement.

4.1. Evidence from infections before and after confinement

To learn more about potentially time-varying effects of WFH on coronavirus infections, we now consider weekly panel data. We observe infection rates for each county over 15 weeks from January 29, 2020 to May 06, 2020. All German federal states simultaneously imposed confinement measures on March 23 in a coordinated way, except for Bavaria, which started the lockdown already on March 21. Thus, in our data confinement is present during sample weeks 8–15.²⁴ We regress the weekly log infection rate on a set of terms interacting week dummies with *WFH freq*, controlling for a full set of county and week fixed effects and the log spatial infection rate. We also account for weekly precipitation, as rainfall might affect compliance with stay-at-home orders and local humidity conditions are likely to influence the transmission of the virus (Mecenas et al., 2020; Lowen and Steel, 2014).²⁵

$$\log i_{it} = \sum_{t=1}^T \beta_t \text{WFH}_i \times t + \gamma' X_{it} + \delta_i + \delta_t + \varepsilon_{it}. \quad (3)$$

Here $i_{it} = I_{it}/L_i$ is the infection rate (cumulative infections divided by the number of individuals) in county i in period t , β_t captures the week-specific differential effect of *WFH freq* on infection rates, X_{it} is the vector of covariates and δ_i and δ_t are, respectively, county and period fixed effects. County fixed effects control for any unobserved county-specific factors correlated with infections and our WFH measures. We cluster standard errors at the county level. Fig. 1 plots the estimated coefficients β_t and the 95-percent confidence band.

The weekly coefficient estimates in Fig. 1 imply that WFH was particularly effective in reducing infection rates within counties

²¹ See Appendix A.1 for a more detailed description and summary statistics of the RKI data.

²² Results are robust to considering other weeks, see Appendix A.1.

²³ Bargain and Aminjonov (2020) and Barrios et al. (2021) show that compliance to containment policies depends on the level of social capital prior to the crisis.

²⁴ See Appendix A.2 for a detailed description of confinement measures in Germany.

²⁵ To construct county-level rainfall, we use precipitation data from the Climate Data Center of the German Weather Service (*Deutscher Wetterdienst*). Daily observations of precipitation height are recorded at the station level. We interpolate the data to county centroids using inverse distance weighting from stations located within a radius of 30 km. We compute weekly rainfall by averaging the daily values between consecutive Wednesdays.

Table 3
The Effect of Working from Home on SARS-CoV-2 Infections across Counties.

	(1)	(2)	(3)	(4)	(5)
<i>WFH feas</i>	−0.045*** (0.011)	−0.043*** (0.014)	−0.045*** (0.011)	−0.053*** (0.011)	−0.045*** (0.014)
R^2	0.54	0.60	0.58	0.62	0.65
NUTS-3 regions	401	399	391	401	389
<i>WFH occ</i>	−0.061*** (0.014)	−0.054*** (0.018)	−0.060*** (0.015)	−0.069*** (0.014)	−0.060*** (0.019)
R^2	0.55	0.60	0.59	0.62	0.66
NUTS-3 regions	401	399	391	401	389
<i>WFH freq</i>	−0.12*** (0.032)	−0.072* (0.041)	−0.11*** (0.034)	−0.12*** (0.035)	−0.081* (0.045)
R^2	0.55	0.60	0.58	0.61	0.65
NUTS-3 regions	401	399	391	401	389
Set of Controls					
Baseline	×	×	×	×	×
Economy		×			×
Health			×		×
Social Capital				×	×

Notes: Dependent variable is the SARS-CoV-2 infection rate (in logs) up to May 06, 2020 (the alleviation date of the first confinement) based on data from the Robert-Koch-Institut. WFH is the percentage share of employees in the county with jobs that are suitable for telework (*WFH feas*) or who either at least occasionally (*WFH occ*) or frequently (*WFH freq*) worked from home in 2018. Observations correspond to NUTS-3 regions (counties) and estimates are weighted based on population size. *Baseline* controls include region-specific log population, log settled area, log GDP, the number of days since the first infection and log spatial infection rates defined as a weighted mean of infection rates in other counties using inverse distances as weights. *Economy* controls include the region-specific fraction of (in- and outward) commuters in the local workforce, an infrastructure index that captures reachability of airports, the fraction of households with broadband internet access (≥ 50 Mbps), the fraction of low-income households ($\leq$ EUR 1,500 per month), the share of workers employed in services, manufacturing, and wholesale/retail sectors, respectively. *Health* controls include the fraction of male population, the fractions of population in working age (15–64 yrs.) and elderly (≥ 65 yrs.), the expected remaining lifetime of people with age 60, the death rate, intensive-care-unit beds per 100,000 inhabitants and hospitals per 100,000 inhabitants. *Social Capital* controls include crime rates, voter turnout, vote shares of populist parties and the number of all registered associations per capita. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

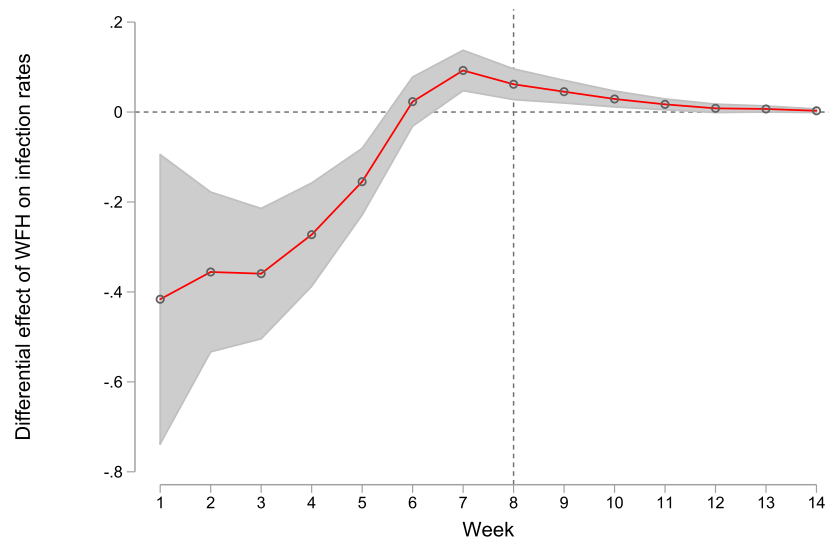


Fig. 1. The Effect of Working from Home on Infection Rates over Time. Notes: The Figure plots coefficient estimates of $WFH_i \times t$ (using *WFH freq*, the percentage share of employees in the county with jobs that frequently do telework) on log infection rates by week (week 15 is absorbed by fixed effects). The dashed vertical line for week 8 indicates the week when the majority of confinement rules were set into force by federal states. The gray shaded area corresponds to 95-percent confidence intervals (with clustering at the county level).

at the earliest stage of the pandemic. Weekly coefficients of WFH are negative and significant at the one-percent level for the first five sample weeks only and after that the differential effect of WFH vanishes. Furthermore – presumably because there are fewer COVID-19 cases during the beginning of the pandemic – confidence bands are substantially wider for the earlier weeks. The null hypothesis that the weekly WFH coefficients during pre-confinement weeks 1–7 are identical to those in weeks 8–14, after confinement rules were implemented by state governments, can

be clearly rejected ($F = 28.80, p < 0.01$). Our finding that WFH is particularly effective at the beginning of the pandemic prior to the confinement, lends empirical support to the epidemiological modeling studies that suggest a higher effectiveness of WFH in containing SARS-CoV-2 at low levels of infections (see Koo et al., 2020).

In the Appendices A.6 and A.7, we provide further robustness checks for the dynamic impact of WFH on infections. First, we estimate a simple difference-in-differences specification where we

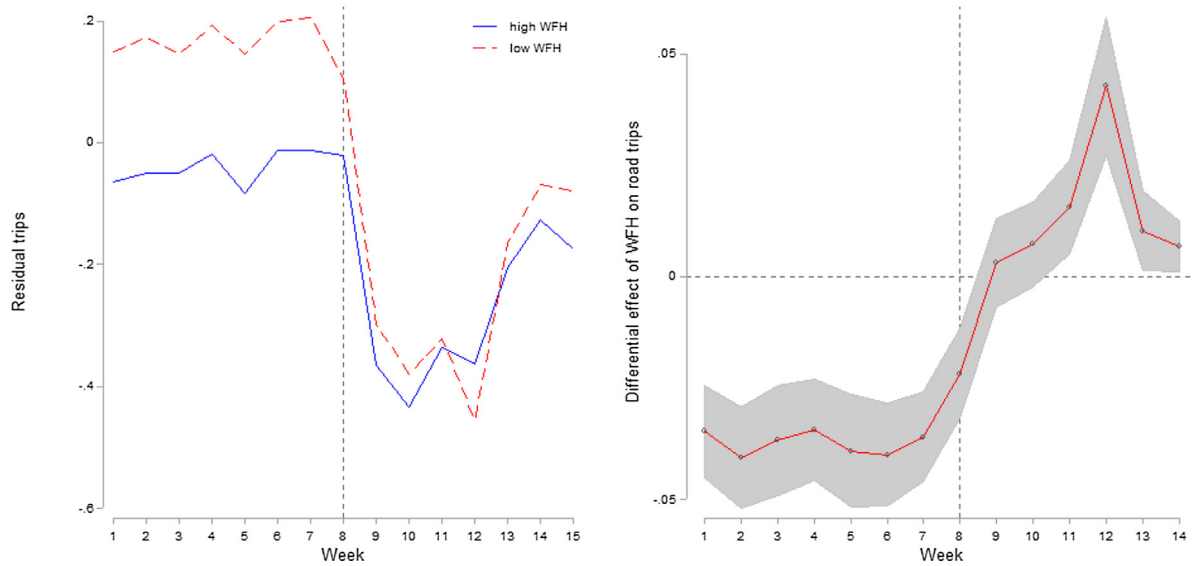


Fig. 2. Working from Home and Decline in Regional Mobility. *Notes:* The left graph shows the development of average road mobility during the COVID-19 crisis. High WFH (solid blue line) includes counties within top 20 percent of *WFH freq*, low WFH (dashed red line) includes counties within bottom 20 percent of *WFH freq*. Average mobility is the mean residual log number of road trips within a county during each week after controlling for log GDP, log population and log area. The right graph plots coefficient estimates of $WFH_i \times t$ (using *WFH freq*.) on log number of road trips by week from week 1: Jan 23 – Jan 29, 2020 to week 15: Apr 29 – May 06, 2020 (week 15 is absorbed by fixed effects). The dashed vertical line for week 8 indicates the week when the majority of confinement rules were set into force by federal states. The gray shaded area corresponds to 95-percent confidence intervals (with clustering at the county level).

interact our WFH measures with a *preconfinement* dummy (weeks 1–7) and find a relatively larger effect of WFH on reducing infection rates before confinement rules came into effect. Second, we show the higher pre-confinement effectiveness of WFH is independent of local differences in confinement strictness. Lastly, we estimate a flexible dynamic spatial count model of disease transmission, based on a modeling approach from the epidemiological literature (Höhle, 2015). Compared to the panel estimates, this model has the following two advantages: *i.* it properly accounts for disease dynamics by including an autoregressive component of infections and *ii.* at the same time it accounts for spatial correlation across counties. The estimates from this model confirm that WFH caused stronger health benefits before confinement was in place.

4.2. Evidence from changes in mobility patterns

To explore the mechanism why WFH was particularly effective in reducing infection rates during the early stages of the pandemic, we now consider adjustments in mobility patterns within counties over time. To study traffic movements, we use cell phone tracking data from Teralytics, a company that provides anonymized geolocation data of German cell phone users and identifies distinct trips by mode of transportation (motorized private transport, train and plane).²⁶ Our measure of interest is the log of total weekly road trips by car within counties.²⁷ The data only report trips with a minimum length of 30 min and a minimum distance of 30 km. Due to their nature, the majority of these trips is likely to be work-related and does not just capture recreational traffic. Between the end of January and the beginning of May, road mobility declined steeply in most counties (see Appendix A.9). To test for the role of WFH in reduced mobility, the left panel of Fig. 2 plots the development of average residual road traffic within counties over time separately

for regions with many and few teleworkable jobs. Average mobility is the mean residual log number of road trips within a county during a given week after controlling for GDP, population and settled area (all in logs). High WFH (solid blue line) includes counties in the top 20 percentile of *WFH freq* and low WFH (dashed red line) includes counties in the bottom 20 percentile of *WFH freq*.²⁸

The time series show that regions with a higher share of teleworkable jobs experienced a lower level of traffic before the confinement after controlling for confounding factors.²⁹ Once confinement rules were implemented, there was a sudden overall decline in the level of road traffic in both groups of counties. While traffic was lower in high-WFH counties before confinement, counties experienced a convergence in traffic levels during the confinement, so that the drop in the number of road trips was larger in low-WFH regions. Towards the end of the confinement, traffic levels begin to move apart again. One explanation for this convergence in traffic patterns is the previously established association between WFH and STW. During the pandemic 30 percent of employees in Germany were on short-time work. Once a large fraction of workers stayed at home independently of whether they worked from there, the traffic-reducing effect of WFH became irrelevant. This interpretation is supported by the estimation results shown in the right panel of Fig. 2. Similarly to the empirical infections model, we present weekly coefficient estimates of WFH based on the following specification:

$$\log T_{it} = \sum_{t=1}^T \beta_t WFH_i \times t + \gamma' X_{it} + \delta_i + \delta_t + \varepsilon_{it}. \quad (4)$$

Here T_{it} is the number of weekly road trips in county i during period t , β_t captures the week-specific effect of *WFH freq*, X_{it} is the vector of covariates and δ_i and δ_t are, respectively, county and period fixed effects. The vector of covariates includes weekly rainfall and interactions of week dummies with the share of commuters in the

²⁶ Teralytics is a Swiss company founded as a spin-off of the ETH Zurich and specialized in the collection and analysis of mobile network data. The company website is accessible at www.teralytics.net.

²⁷ We also consider commuting traffic by train in the Appendix.

²⁸ A similar pattern is visible when using different cutoff levels for *WFH freq* such as above/below the median or the top/bottom 10 percent.

²⁹ This is consistent with US evidence showing that local variation in the opportunity to do telework is a determinant for mobility levels (Brough et al., 2020).

county. The right panel of Fig. 2 plots the estimated coefficients β_i . The Figure confirms that the differential effect of WFH on reducing mobility was particularly large before the confinement. Again, the null hypothesis that the weekly WFH coefficients during pre-confinement weeks are identical to those in weeks after confinement was implemented can be clearly rejected ($F = 51.40, p < 0.01$). Also here, we see that the mobility-reducing effect of WFH over time increases again towards the end of the confinement period, when businesses started to operate again. In Appendix A.9 we estimate the same model using commuter train traffic as an alternative outcome variable and obtain qualitatively similar results.

5. Conclusions

In the wake of the COVID-19 pandemic, much of the policy debate has been concerned with weighing the short-run economic and social costs of non-pharmaceutical interventions to contain the virus against their potential public health benefits. In this paper, we have argued that working from home is a particularly effective NPI because it allows to reduce infection risk while maintaining economic activity: all else equal, we have found that regions, industries and firms with a higher WFH potential reported significantly fewer short-time work filings during the first wave of the pandemic in spring 2020. At the same time, counties with a higher share of teleworkable jobs also experienced significantly fewer COVID-19 cases. The magnitudes of our estimates suggest that WFH also has positive spill-over effects to workers without the possibility to work from home, both in terms of labor-market effects and infection risks. Nonetheless, as highly skilled workers currently have the greatest possibilities to engage in telework, this unequal access to WFH is likely to reinforce pre-existing inequality along socioeconomic dimensions. Moreover, we have shown that WFH was less important in reducing infections after confinement was imposed by authorities, in line with observed mobility patterns from cell-phone tracking data. Thus, confinement and WFH are to some extent substitutable containment measures. This implies that WFH should be encouraged as long as significant infection risk remains.

Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at <https://doi.org/10.1016/j.jpubeco.2021.104373>.

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