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# My Home Is My Castle – The Benefits of Working from Home During a Pandemic Crisis

## Evidence from Germany

*Jean-Victor Alipour, Harald Fadinger, Jan Schymik*

ifo INSTITUTE
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at the University of Munich

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Poschingerstr. 5, 81679 Munich, Germany
Telephone +49(0)89 9224 0, Telefax +49(0)89 985369, email ifo@ifo.de
www.ifo.de

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# My Home Is My Castle – The Benefits of Working from Home During a Pandemic Crisis: Evidence from Germany*

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 SARSCoV-2 infections and short-time work registrations, firm- and employee-level surveys and cell phone tracking data on mobility patterns, we find that working from home 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.

JEL Code: J22, H12, I18, J68, R12, R23
Keywords: COVID-19, SARS-CoV-2, working from home, labor supply shock, infections, mitigation, BIBB-BAuA

Jean-Victor Alipour
ifo Institute – Leibniz Institute for Economic Research
at the University of Munich,
University of Munich
Poschingerstr. 5
81679 Munich, Germany
alipour@ifo.de

Harald Fadinger
University of Mannheim
Department of Economics
68161 Mannheim, Germany,
Centre for Economic Policy Research (CEPR)
harald.fadinger@uni-mannheim.de

Jan Schymik
University of Mannheim
Department of Economics
68161 Mannheim, Germany
jschymik@mail.uni-mannheim.de

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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 there is little trade-off between fighting the pandemic and stabilizing the economy in the medium term (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 interactions 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 teleworkablity 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 applications for around 30% 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 short-time

[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).

work.[5] A 1 p.p. increase in the share of teleworkable jobs at the county level reduces short-time work 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]

[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 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.

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 potentially 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 low WFH potential are less educated, have lower income and fewer liquid assets. Using real-time survey data, Adams-Prassl et al. (2020a) 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 status 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

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

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

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

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% of employees worked from home on a regular basis, 26% did so at least occasionally, and 56% 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% 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 (STW) 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% instead of laying them off. Up to 67% 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% 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 put

[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).

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 both more STW applications, as more 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, health care 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 *Economy* controls to account for more detailed regional differences in economic activity beyond GDP. These 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 ($\geq$ 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 health care 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 ($\geq$ 65 yrs.), remaining life expectancy at age 60, the death rate, the number 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 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 our 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'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

[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) |
|---|---|---|---|---|---|
| *WFH feas* | -1.22*** | -0.70*** | -1.28*** | -1.24*** | -0.84*** |
| | (0.22) | (0.21) | (0.23) | (0.25) | (0.24) |
| $R^2$ | 0.23 | 0.33 | 0.27 | 0.28 | 0.36 |
| NUTS-3 regions | 401 | 399 | 391 | 401 | 389 |
| *WFH occ* | -1.70*** | -1.15*** | -1.81*** | -1.88*** | -1.46*** |
| | (0.24) | (0.23) | (0.25) | (0.27) | (0.29) |
| $R^2$ | 0.27 | 0.35 | 0.30 | 0.31 | 0.38 |
| NUTS-3 regions | 401 | 399 | 391 | 401 | 389 |
| *WFH freq* | -3.34*** | -2.20*** | -3.48*** | -3.69*** | -2.60*** |
| | (0.50) | (0.51) | (0.54) | (0.60) | (0.65) |
| $R^2$ | 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 of 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 ($\geq$ 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 ($\geq$ 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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 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:

$$y_{isc} = \beta_0 + \beta_1 \times \mathit{telework}_{isc} + \delta' X_{isc} + \alpha_c + \varepsilon_{isc} \tag{1}$$

$$\mathit{telework}_{isc} = \pi_0 + \pi_1 \times \mathit{WFHfeas}_s + \lambda' X_{isc} + \alpha_c + v_{isc}, \tag{2}$$

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 $\mathit{telework}_{isc}$ is a dummy indicator for firms who increased telework in April 2020. The regressions also include county fixed effects ($\alpha_c$) 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 A10 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 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

[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).

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 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 between 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 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 demand-shock. 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 on site. This directly lowers the contact rate – defined as the average number of contacts

[20] Table A9 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) |
| *Panel A: Participated in Short-Time Work Scheme* | | | | | | |
| **Intensified Telework** | | | -12.41*** | -5.40*** | -71.55*** | -49.42*** |
| | | | (4.00) | (1.99) | (11.34) | (13.80) |
| **WFH feas** | -0.81*** | -0.45*** | | | | |
| | (0.20) | (0.12) | | | | |
| **Mandatory shutdown** | | 29.58*** | | 34.58*** | | 20.64*** |
| | | (5.68) | | (6.00) | | (6.46) |
| **State of business 2019Q4** | | | | | | |
| negative | | 11.98*** | | 12.08*** | | 10.69*** |
| | | (1.74) | | (1.81) | | (1.91) |
| positive | | -9.92*** | | -10.39*** | | -9.77*** |
| | | (1.71) | | (1.79) | | (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 |
| *Panel B: Negative Corona Shock* | | | | | | |
| **Intensified Telework** | | | -14.74*** | -6.57** | -74.72*** | -39.13*** |
| | | | (5.04) | (2.54) | (14.80) | (13.84) |
| **WFH feas** | -0.86*** | -0.37*** | | | | |
| | (0.26) | (0.12) | | | | |
| **Mandatory shutdown** | | 40.58*** | | 43.93*** | | 33.94*** |
| | | (7.18) | | (7.60) | | (6.40) |
| **State of business 2019Q4** | | | | | | |
| negative | | 11.01*** | | 11.00*** | | 9.86*** |
| | | (2.66) | | (2.77) | | (2.98) |
| positive | | -9.16*** | | -9.56*** | | -9.34*** |
| | | (1.99) | | (2.00) | | (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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

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

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *WFH feas* | -0.045*** | -0.043*** | -0.045*** | -0.053*** | -0.045*** |
| | (0.011) | (0.014) | (0.011) | (0.011) | (0.014) |
| $R^2$ | 0.54 | 0.60 | 0.58 | 0.62 | 0.65 |
| NUTS-3 regions | 401 | 399 | 391 | 401 | 389 |
| *WFH occ* | -0.061*** | -0.054*** | -0.060*** | -0.069*** | -0.060*** |
| | (0.014) | (0.018) | (0.015) | (0.014) | (0.019) |
| $R^2$ | 0.55 | 0.60 | 0.59 | 0.62 | 0.66 |
| NUTS-3 regions | 401 | 399 | 391 | 401 | 389 |
| *WFH freq* | -0.12*** | -0.072* | -0.11*** | -0.12*** | -0.081* |
| | (0.032) | (0.041) | (0.034) | (0.035) | (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 ($\geq$ 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 ($\geq$ 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 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, 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. To illustrate the quantitative implication of the estimates consider the following thought experiment: If Berlin, a county with a rather high share of *WFH freq* jobs (11.72%) 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

[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.6.

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 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* ad 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.

[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.

### 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, the log spatial infection rate and weekly rainfall.[25]

$$\log i_{it} = \sum_{t=1}^{T} \beta_t WFH_i \times t + \gamma' X_{it} + \delta_i + \delta_t + \varepsilon_{it}. \tag{3}$$

Here $i_{it} = I_{it}/L_i$ is the infection rate (cumulative infections divided by the number of individuals) in county $i$ in period $t$, $\beta_t$ captures the week-specific differential effect of *WFH freq* on infection rates, $X_{it}$ is the vector of covariates and $\delta_i$ and $\delta_t$ 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. Figure 1 plots the estimated coefficients $\beta_t$ and the 95-percent confidence band.

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

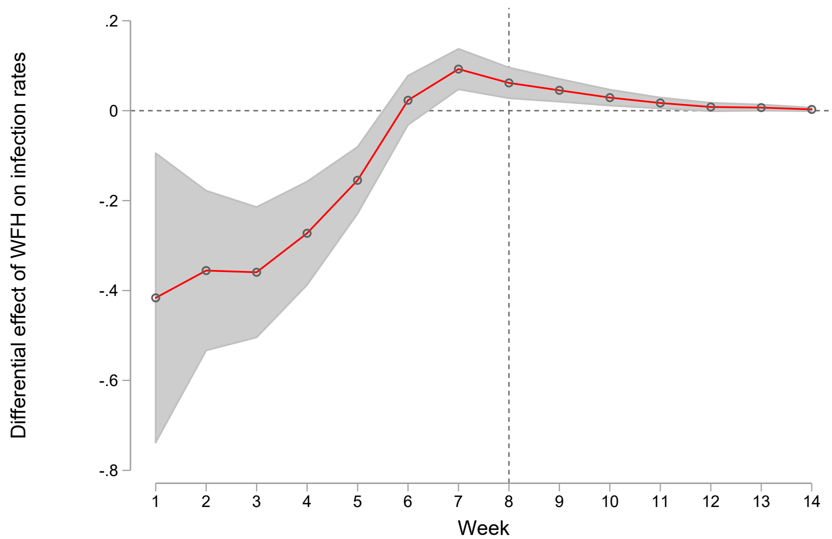
In the Appendices A.6 and A.7, we provide further robustness checks for the dynamic impact of WFH on infections. First, we estimate a simple difference-in-differences specification where we interact our WFH measures with a *pre confinement* dummy (weeks 1-7) and find a relatively larger effect of WFH 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,

[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 kilometers. We compute weekly rainfall by averaging the daily values between consecutive Wednesdays.

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.

Figure 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).

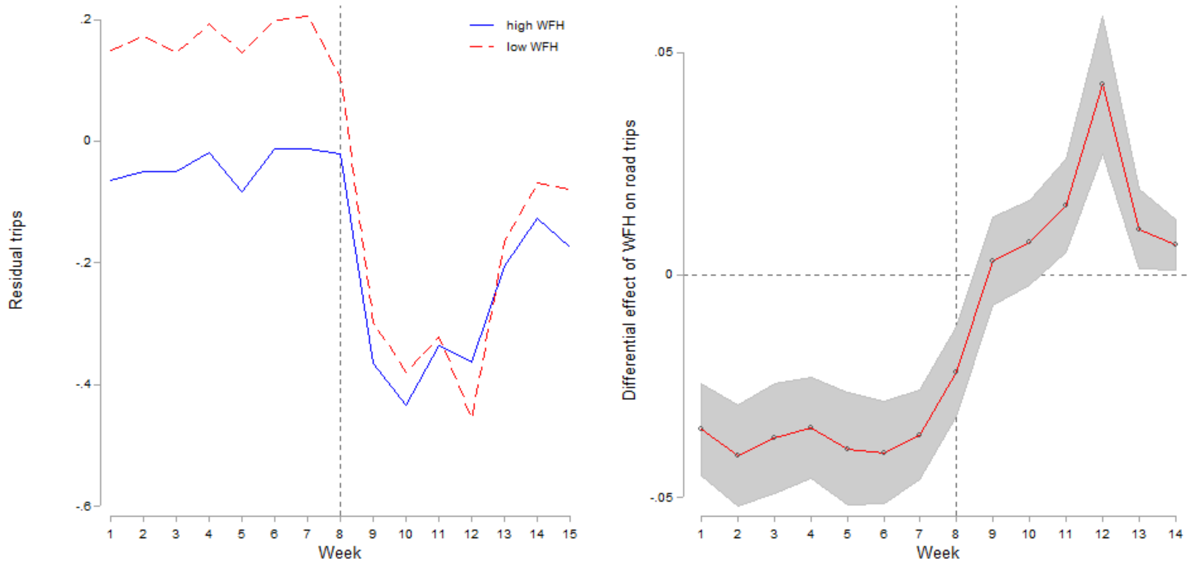
## 4.2 Evidence from Changes in Mobility Patterns

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 geo-location 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 minutes and a minimum distance of 30 kilometers. Due to their nature, the majority of these trips is likely to be work-related and does not just capture recreational traffic.

[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.

Figure 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% of *WFH freq*, low WFH (dashed red line) includes counties within bottom 20% 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).

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 Figure 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

[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%.

[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).

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% 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 Figure 2. Similarly to the empirical infections model, we present weekly coefficient estimates of WFH based on the following specification:

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

Here $T_{it}$ is the number of weekly road trips in county $i$ during period $t$, $\beta_t$ captures the week-specific effect of *WFH freq*, $X_{it}$ is the vector of covariates and $\delta_i$ and $\delta_t$ 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 county. The right panel of Figure 2 plots the estimated coefficients $\beta_t$. 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.

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# A Internet Appendix (For Online Publication)

## Contents

## A.1 Data Descriptions and Summary Statistics

Table A1: Summary Statistics of County-Level Variables

| | Mean | SD | Min | p25 | Median | p75 | Max | N | Source |
|---|---|---|---|---|---|---|---|---|---|
| **Outcome variable** | | | | | | | | | |
| Share of STW in March/April 2020 | 33.00 | 7.73 | 11.84 | 27.27 | 32.39 | 37.63 | 74.42 | 401 | BA 2019/2020 |
| **WFH measures** | | | | | | | | | |
| WFH feasible (WFH feas) | 52.69 | 4.18 | 45.55 | 49.73 | 51.50 | 54.82 | 67.47 | 401 | BIBB/BAuA Survey 2018, BA June 2019 |
| WFH at least occasionally (WFH occ) | 23.52 | 3.04 | 18.40 | 21.47 | 22.54 | 24.82 | 36.14 | 401 | BIBB/BAuA Survey 2018, BA June 2019 |
| WFH frequently (WFH freq) | 8.47 | 1.33 | 5.98 | 7.56 | 8.02 | 8.99 | 14.30 | 401 | BIBB/BAuA Survey 2018, BA June 2019 |
| WFH index (Dingel and Neiman, 2020) | 33.33 | 4.92 | 24.71 | 30.01 | 31.92 | 35.79 | 50.65 | 401 | Dingel and Neiman (2020) |
| **Baseline controls** | | | | | | | | | |
| Days since first Covid case (30 April) | 65.17 | 10.51 | 48.00 | 58.00 | 63.00 | 68.00 | 95.00 | 401 | RKI |
| log spatial infection rate (29 April) | -1.62 | 0.19 | -1.93 | -1.76 | -1.67 | -1.44 | -1.02 | 401 | RKI |
| log GDP | 15.53 | 0.76 | 13.92 | 14.99 | 15.45 | 15.94 | 18.75 | 401 | FSO, 2017 |
| log settled area | 8.82 | 0.67 | 6.95 | 8.50 | 8.84 | 9.29 | 10.81 | 401 | FSO, Dec. 2018 |
| log total population | 11.98 | 0.66 | 10.44 | 11.55 | 11.95 | 12.40 | 15.11 | 401 | FSO Dec. 2018 |
| **Economy controls** | | | | | | | | | |
| Employment share in Wholesale/Retail | 13.96 | 3.09 | 4.76 | 11.90 | 13.68 | 15.49 | 25.37 | 401 | BA June 2019 |
| Employment share in Manufacturing | 23.79 | 10.37 | 2.02 | 16.02 | 22.67 | 31.28 | 57.83 | 399 | BA June 2019 |
| Employment share in Services | 66.51 | 10.85 | 36.73 | 58.39 | 66.68 | 74.47 | 92.36 | 401 | BA June 2019 |
| Driving dist. to nearest airport (mins) | 49.62 | 21.98 | 6.00 | 33.00 | 48.00 | 65.00 | 122.00 | 401 | BBSR, 2018 |
| Broadband coverage (50+ Mbps downl.) | 76.67 | 15.45 | 27.40 | 67.30 | 77.10 | 90.50 | 99.60 | 401 | BBSR, 2017 |
| Share of commuters | 0.83 | 0.31 | 0.30 | 0.60 | 0.78 | 0.97 | 2.33 | 401 | BA June 2019 |
| Share of low-income households | 30.64 | 6.03 | 9.30 | 26.40 | 30.50 | 35.20 | 44.10 | 401 | BBSR, 2016 |
| **Health controls** | | | | | | | | | |
| Hospitals per 100T inhabitants | 2.51 | 1.48 | 0.34 | 1.53 | 2.22 | 3.08 | 9.80 | 396 | FSO, 2017 |
| ICU beds per 100T inhabitants | 41.33 | 34.51 | 4.40 | 18.53 | 31.54 | 50.48 | 239.47 | 394 | DIVI Register |
| Share of working age population (15-64) | 0.67 | 0.02 | 0.60 | 0.66 | 0.67 | 0.68 | 0.74 | 401 | FSO Dec. 2018 |
| Deaths per 1000 inhabitants | 11.81 | 1.89 | 7.50 | 10.40 | 11.70 | 13.00 | 17.10 | 401 | BBSR, 2017 |
| Remaining life expectancy at age 60 | 23.70 | 0.66 | 22.02 | 23.27 | 23.68 | 24.18 | 25.72 | 401 | BBSR, 2017 |
| Share of inhabitants aged 65 and above | 0.22 | 0.03 | 0.16 | 0.20 | 0.22 | 0.24 | 0.32 | 401 | FSO, Dec. 2018 |
| Share of male inhabitants | 0.49 | 0.01 | 0.47 | 0.49 | 0.49 | 0.50 | 0.51 | 401 | FSO, Dec. 2018 |
| **Social Capital controls** | | | | | | | | | |
| Election turnout, Federal Election 2017 | 75.08 | 3.79 | 63.10 | 72.70 | 75.30 | 77.60 | 84.10 | 401 | BBSR, 2017 |
| Vote share for far left, Fed. Elec. 2017 | 8.82 | 4.54 | 3.60 | 5.70 | 6.80 | 10.30 | 23.30 | 401 | BBSR, 2017 |
| Vote share for far right, Fed. Elec. 2017 | 13.39 | 5.33 | 4.90 | 9.80 | 12.00 | 15.30 | 35.50 | 401 | BBSR, 2017 |
| Crimes per 100T inhabitants | 5,658 | 2,292 | 2,299 | 3,940 | 5,222 | 6,896 | 15,194 | 401 | BKA, 2019 |
| Non-profit associations per 100T inhab. | 688 | 197 | 100 | 567 | 667 | 781 | 1,734 | 401 | Franzen and Botzen (2011) |

*Notes:* The Table reports summary statistics and the source of county-level variables used in our analyses. Share of short-time work (STW) applications in March and April 2020 is measured relative to June 2019 employment. See Section 2.1 for details on the construction of our WFH measures. FSO = Federal Statistical Office (*Statistische Ämter des Bundes und der Länder*); BBSR = Federal Institute for Research on Building, Urban Affairs and Spatial Development (*Bundesinstitut für Bau-, Stadt- und Raumforschung*); BA = Federal Employment Agency (*Bundesagentur für Arbeit*); RKI = Robert Koch Institute.

Table A2: Pairwise Correlation between Working from Home and County-Level Variables

| | (1) *WFH feas* | (2) *WFH occ* | (3) *WFH freq* |
|---|---|---|---|
| **Baseline controls** | | | |
| Days since first COVID case | 0.24*** | 0.22*** | 0.18*** |
| log spatial infection rate | 0.14** | 0.089 | -0.0071 |
| log settled area | -0.22*** | -0.17*** | -0.14** |
| log total population | 0.36*** | 0.39*** | 0.38*** |
| log GDP | 0.60*** | 0.61*** | 0.56*** |
| **Economy controls** | | | |
| Share of commuters | 0.55*** | 0.53*** | 0.48*** |
| Reachability of airports | -0.43*** | -0.43*** | -0.40*** |
| Broadband coverage | 0.65*** | 0.61*** | 0.55*** |
| Employment shr. manufacturing | -0.35*** | -0.41*** | -0.52*** |
| Employment shr. wholesale / retail | -0.096 | -0.099* | -0.092 |
| Employment shr. services | 0.54*** | 0.59*** | 0.68*** |
| Share of low-income households | -0.070 | -0.015 | 0.12* |
| **Health controls** | | | |
| Share of males | -0.32*** | -0.32*** | -0.37*** |
| Share of inhabitants aged 65 and above | -0.46*** | -0.43*** | -0.36*** |
| Share of working age population (15-64) | 0.49*** | 0.47*** | 0.41*** |
| Remaining life expectancy at age 60 | 0.33*** | 0.34*** | 0.30*** |
| Deaths per 1000 inhabitants | -0.47*** | -0.46*** | -0.39*** |
| ICU beds per 100T inhabitants | 0.33*** | 0.34*** | 0.39*** |
| Hospitals per 100T inhabitants | 0.040 | 0.032 | 0.053 |
| **Social Capital controls** | | | |
| Non-profit associations per 100T inhab. | 0.15** | 0.15** | 0.18*** |
| Crimes per 100T inhabitants | 0.46*** | 0.47*** | 0.54*** |
| Election turnout, federal election 2017 | 0.20*** | 0.20*** | 0.13** |
| Vote share for far right, fed. elec. 2017 | -0.33*** | -0.29*** | -0.22*** |
| Vote share for far left, fed. elec. 2017 | 0.037 | 0.11* | 0.24*** |

*Notes:* The Table reports pairwise correlation coefficients between our WFH measures and individual control variables at the county-level. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.5$

Table A3: Summary statistics of the ifo Business Survey data

| | Min | Mean | Max | SD | N |
|---|---|---|---|---|---|
| **Outcome variables** | | | | | |
| Applied for short-time work | 0 | 0.478 | 1 | 0.500 | 6,840 |
| Very negative Covid-19 impact | 0 | 0.297 | 1 | 0.457 | 6,095 |
| **Explanatory variables** | | | | | |
| Intensified telework | 0 | 0.611 | 1 | 0.487 | 6,840 |
| WFH feas | 29.58 | 54.83 | 89.55 | 13.72 | 7,291 |
| Mandatory shutdown | 0 | 0.157 | 1 | 0.364 | 7,291 |
| Demand drop due to Covid-19, sector avg. (3/20) | 0 | 0.458 | 1 | 0.230 | 5,352 |
| Business state (2019Q4) | -1 | 0.240 | 1 | 0.671 | 6,654 |
| Business outlook (2019Q4) | -1 | -0.123 | 1 | 0.591 | 6,648 |
| Export share (9/18) | 0 | 0.146 | 1 | 0.208 | 7,291 |
| Firm size bins (2/20) | | | | | |
| 1-9 employees | 0 | 0.144 | 1 | 0.351 | 6,651 |
| 10-49 employees | 0 | 0.378 | 1 | 0.485 | 6,651 |
| 50-99 employees | 0 | 0.153 | 1 | 0.360 | 6,651 |
| 100-249 employees | 0 | 0.140 | 1 | 0.347 | 6,651 |
| >249 employees | 0 | 0.185 | 1 | 0.388 | 6,651 |
| Survey ID | | | | | |
| Construction | 0 | 0.151 | 1 | 0.358 | 7,291 |
| Services | 0 | 0.297 | 1 | 0.457 | 7,291 |
| Wholesale/Retail | 0 | 0.249 | 1 | 0.432 | 7,291 |
| Manufacturing | 0 | 0.304 | 1 | 0.460 | 7,291 |

*Notes:* The Table reports summary statistics of the April 2020 wave of the ifo Business Survey used in our firm-level analysis. The sample is complemented with averages of survey responses on business expectations and business conditions in Q4 of 2019 (elicited on three-point Likert scales), leave-one-out industry averages (employment weighted) of firms reporting a demand drop due to COVID-19 in March 2020 as well as firms' export share as of September 2018 and firm size in terms of employment elicited in February 2020.

### A.1.1 Measuring Working from Home in Germany

This section provides a description of the construction of our three WFH measures at the county and industry level. In particular, we follow Alipour et al. (2020) and combine data from two sources: *i.* Employee-level information from the 2018 wave of the BIBB/BAuA Employment Survey and *ii.* Occupational employment counts at the county and industry level provided by the Federal Employment Agency (*Bundesagentur für Arbeit*). The BIBB/BAuA survey is jointly carried out by the German Federal Institute for Vocational Education and Training (BIBB) and the German Federal Institute for Occupation Safety and Health (BAuA). The 2018 wave contains rich information about 20,012 individuals surveyed between October 2017 and April 2018; for more details see Hall et al. (2020). In particular, the survey contains information about employee characteristics, the nature of their jobs and also reports about employees' work from home habits. Based on this information, we compute three measures: An indicator variable that identifies individuals who work from home "always" or "frequently" (*WFH freq*). Second, an indicator for respondents who report working at home at least occasionally (*WFH occ*). And third, a dummy identifying employees who ever work from home or who do not exclude the possibility of home-based work, provided the company grants the option (*WFH feas*). The latter measure hence identifies jobs that can (at least partly) be done from home, independently of a worker's previous teleworking experience.

To derive the geographical and industry-level distribution of teleworkable jobs, we collapse our WFH indicators to the occupational level, based on 36 KldB-2010 2-digit occupations (excluding military services), and combine the resulting shares with administrative employment data for each county (401 *Kreise and kreisfreie Städte*) and each industry (2-digit NACE rev. 2), respectively. Specifically, the WFH potential of county $c$ is given by

$$WFH_c = \sum_o s_{oc} \times WFH_o, \tag{5}$$

where $o$ denotes occupations and $s_{oc}$ is the employment share of occupation $o$ in county $c$. $WFH_o$ in turn denotes the occupation-specific WFH share. Analogously, the WFH potential of industry $i$ is given by

$$WFH_i = \sum_o s_{oi} \times WFH_o, \tag{6}$$

where $s_{oi}$ denotes the employment share of occupation $o$ in industry $i$.

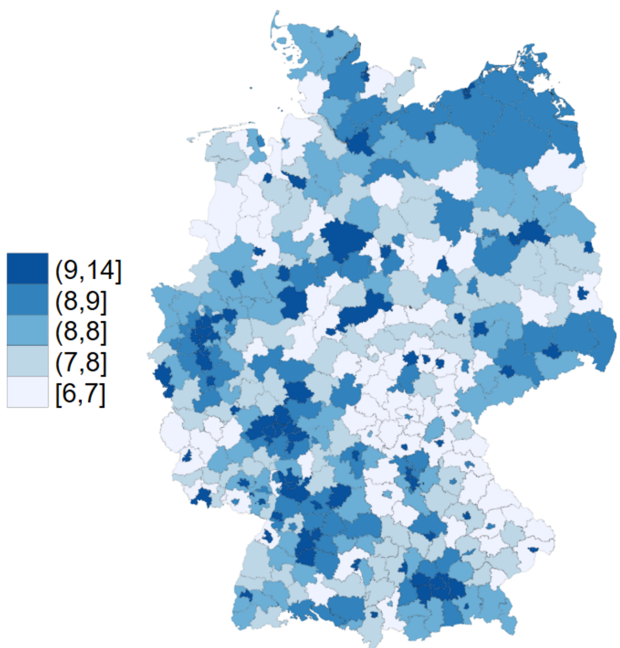
Table A4 reports the occupation-specific WFH shares for each of our three measures. Figure A1 display the geographical distribution of teleworkable jobs as measured by *WFH freq*. A potential advantage of the survey-based approach to measure WFH potentials compared to relying on information about the task content of occupations (as proposed by Dingel and Neiman, 2020) is that assessments about the possibility to WFH are independent of researchers' plausibility judgments. In Section A.8, we document that our measures are still highly correlated with Dingel and Neiman's task-based WFH index and show that our results do not hinge on the measure of WFH employed.

Table A4: WFH Shares by Occupation

| | **Occupations (KldB 2010 2-digit)** | *WFH freq* | *WFH occ* | *WFH feas* |
|---|---|---|---|---|
| 11 | Occupations in agriculture, forestry, and farming | 7.59 | 14.52 | 30.44 |
| 12 | Occupations in gardening and floristry | 3.03 | 9.13 | 41.25 |
| 21 | Occupations in production and processing of raw materials, glass and ceramic | 0.00 | 6.85 | 16.56 |
| 22 | Occupations in plastic-making and -processing, wood-working and -processing | 1.21 | 4.99 | 28.91 |
| 23 | Occupations in paper-making and -processing, printing & technical media design | 2.98 | 17.60 | 58.23 |
| 24 | Occupations in metal-making and -working, and in metal construction | 0.62 | 3.42 | 22.13 |
| 25 | Technical occupations in machine-building and automotive industry | 4.13 | 14.07 | 45.50 |
| 26 | Occupations in mechatronics, energy electronics and electrical engineering | 8.77 | 28.43 | 58.49 |
| 27 | Occupations in technical R&D, construction, production planning and scheduling | 6.90 | 32.49 | 72.65 |
| 28 | Occupations in textile- and leather-making and -processing | 3.03 | 16.26 | 52.26 |
| 29 | Occupations in food-production and -processing | 4.93 | 12.53 | 28.97 |
| 31 | Occupations in construction scheduling, architecture and surveying | 10.49 | 38.57 | 81.92 |
| 32 | Occupations in building construction above and below ground | 0.80 | 5.73 | 24.17 |
| 33 | Occupations in interior construction | 1.08 | 6.24 | 20.96 |
| 34 | Occupations in building services engineering and technical building services | 3.09 | 14.41 | 34.12 |
| 41 | Occupations in mathematics, biology, chemistry and physics | 4.62 | 22.93 | 55.74 |
| 42 | Occupations in geology, geography and environmental protection | 20.75 | 46.19 | 73.57 |
| 43 | Occupations in computer science, information and communication technology | 23.78 | 75.95 | 96.77 |
| 51 | Occupations in traffic and logistics (without vehicle driving) | 5.12 | 11.96 | 38.06 |
| 52 | Drivers and operators of vehicles and transport equipment | 1.20 | 4.26 | 16.24 |
| 53 | Occupations in safety and health protection, security and surveillance | 4.94 | 15.40 | 39.79 |
| 54 | Occupations in cleaning services | 5.68 | 8.62 | 29.88 |
| 61 | Occupations in purchasing, sales and trading | 28.14 | 55.55 | 89.00 |
| 62 | Sales occupations in retail trade | 3.35 | 11.58 | 40.58 |
| 63 | Occupations in tourism, hotels and restaurants | 11.68 | 21.45 | 43.36 |
| 71 | Occupations in business management and organisation | 14.48 | 44.18 | 86.72 |
| 72 | Occupations in financial services, accounting and tax consultancy | 9.99 | 34.35 | 91.76 |
| 73 | Occupations in law and public administration | 8.97 | 28.10 | 84.23 |
| 81 | Medical and health care occupations | 2.92 | 13.74 | 40.39 |
| 82 | Occupations in non-medical healthcare, body care, wellness & medical technicians | 3.64 | 12.96 | 36.38 |
| 83 | Occupations in education and social work, housekeeping, and theology | 12.79 | 33.71 | 58.92 |
| 84 | Occupations in teaching and training | 64.61 | 85.23 | 91.32 |
| 91 | Occupations in in philology, literature, humanities, social sciences, and economics | 23.47 | 67.07 | 83.45 |
| 92 | Occupations in advertising and marketing, in commercial and editorial media design | 20.12 | 52.72 | 92.02 |
| 93 | Occupations in product design, artisan craftwork, making of musical instruments | 28.64 | 33.19 | 67.68 |
| 94 | Occupations in the performing arts and entertainment | 21.21 | 53.81 | 65.63 |

*Notes:* The Table reports percentage shares of employees who report working from home frequently (*WFH freq*), at least occasionally (*WFH occ*) and who ever work from home or do not exclude the possibility to work from home, provided the employer grants the option (*WFH feas*) for each occupation at the 2-digit level according to the German classification KldB 2010 (*Klassifikation der Berufe*). Data are from the 2018 BIBB/BAuA Employment Survey.

Figure A1: Geographical Distribution of Pre-Crisis Frequent Teleworkers

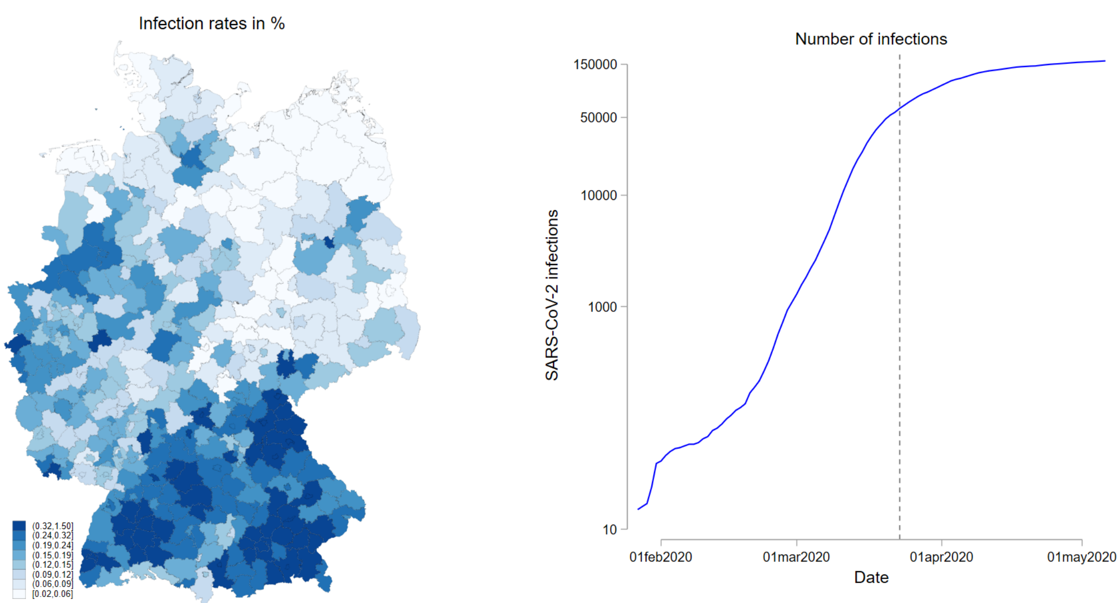



*Notes:* The map depicts the percentage share of pre-crisis frequent teleworkers (*WFH freq*) across NUTS-3 regions (counties) in Germany. Data are from BIBB/BAuA Employment Survey 2018 and the Federal Employment Agency (BA) 2019.

### A.1.2 Measuring SARS-CoV-2 Infections

In Germany, local health authorities are required by law to report suspected cases, infections and proof of the SARS-CoV-2 virus at the county level on a daily basis (*Infektionsschutzgesetz*). This data on cases and fatalities is provided and administered by the Robert-Koch-Institut (RKI). Only cases with a positive laboratory diagnostic are counted, independently of their clinical evidence. After basic verification, this information is transferred electronically by local health authorities to the RKI, at the latest by the next working day. At the RKI, data are validated using an automatic validation algorithm. The RKI processes the reported new cases once a day at midnight and publishes them by the next morning. The final dataset contains daily information on the number of local infections and fatalities by sex and age cohort at the county level, where counties are based on individuals' places of residence. To minimize measurement issues caused by reporting lags over weekends, we consider weekly data measured on Wednesdays. Figure A2 displays the geographical distribution of infection rates as of May 6, 2020 as well as cumulative COVID-19 cases in Germany. Table A5 reports summary statistics of the infection data across counties.

Figure A2: SARS-CoV-2 Infections in Germany




*Notes:* The Figure depicts the distribution of infection rates in % across NUTS-3 regions in Germany for May 06, 2020 (left graph) and the aggregate time series of COVID-19 cases in Germany (right graph). The dashed vertical line indicates the date when strict confinement rules came into effect. Data are from the Robert-Koch-Institut.

Table A5: Summary of Infection Statistics at the County-Level

| | Mean | Std. Dev. | Min | 25th | Median | 75th | Max |
|---|---|---|---|---|---|---|---|
| *Infection Rate in %* | | | | | | | |
| on May 06, 2020 | 0.20 | 0.15 | 0.02 | 0.10 | 0.24 | 0.24 | 1.50 |
| on Sep 30, 2020 | 0.33 | 0.19 | 0.04 | 0.19 | 0.41 | 0.41 | 1.63 |
| *Days since first infection* | | | | | | | |
| on May 06, 2020 | 71.7 | 11.3 | 54 | 64 | 76 | 76 | 101 |

*Notes:* The Table reports descriptive statistics for RKI infection data across 401 NUTS-3 regions in Germany.

## A.2 Description of Confinement Measures During the First Wave of the COVID-19 Pandemic in Germany

**Confinement:** On March 8, federal and state governments recommended the cancellation of all big public events. Governments then agreed on an extensive confinement to restrict social contacts on Sunday, March 22. Most of these rules started to apply from the next Monday, March 23 onward and were planned to stay in force until May 3-4 in most states. There was some regional variation across states regarding the exact timing of confinement: in SN and BY confinement started already on March 21; in BR confinement was planned to stay until May 8, in MV until May 10.

10 states opted for more lax confinement rules (*Kontaktbeschränkungen*). In those states, staying in public was only allowed together with up to one person from another household (while keeping a personal distance of at least 1.5 m) or with members from the same household. In contrast, 6 states (BY, SL, ST, SN, BB, BE) opted for stricter confinement rules (*Ausgangsbeschränkungen*) which prohibited leaving the household without good reason. Reasons were work commutes or shopping for groceries, doctor visits, sport activities and walks (with some exceptions in terms of strictness and timing at the county level).

**Business Closures:** Closures of many stores and church services and playgrounds from Monday, March 16, 2020 onward. Stores providing necessities remained open. Restaurants were free to offer pickup service. Gradual reopening from April 19, onward.

**Schools and Day Care:** With exceptions schools and kindergartens were closed from Monday, March 16 onward.

**Obligatory Face Masks**: From April 27 onward, wearing a mouth-nose mask during public transport or while buying groceries was mandatory.

## A.3 Employee-Level Differences in Access to Work from Home

A nascent literature examines differences in the access to WFH across socioeconomic characteristics. A distinct feature that distinguishes employees with and without the possibility to work from home is the level of education (Adams-Prassl et al., 2020b; Alipour et al., 2020; Mongey et al., 2020; Yasenov, 2020). For instance, in the BIBB/BAuA Survey, employees without a university degree are only half as likely to have a teleworkable job and nearly four times less likely to have teleworking experience before the pandemic. Apart from the educational disparity, this group appears also disproportionately more vulnerable in term of other socioeconomic dimensions, such as income and the ownership of liquid assets. The differences in access to WFH are mainly attributable to different job task requirements that distinguish teleworkable from non-teleworkable jobs; in particular, a high task content of cognitive, non-manual tasks, which are typically performed by higher-skilled labor (Alipour et al., 2020; Mergener, 2020).

We shed some additional light on the potential inequalities in access to WFH during the pandemic by estimating WFH as a function of demographic and workplace characteristics as well as a set of occupation and sector fixed effects. Table A6 reports the results for the outcome variables *WFH freq*, which identifies employees reporting frequently working from home (Columns 1-3), and *WFH feas*, which identifies employees with a teleworkable job (Columns 4-6).[30] Occupational variation alone explains 21% and 27% of the variation in *WFH freq* and *WFH feas*, respectively (Columns 1 and 4). Adding individual characteristics (Columns 2 and 5) and a set of industry dummies (Columns 3 and 6) does not substantially add to the overall explanatory power in terms of $R^2$. We find no statistically significant gender differences in WFH usage or access, holding other characteristics constant. An employee's age is correlated with WFH at a statistically significant level, however, the magnitude of the estimates appear very small. Holding a university degree is very strongly associated with having a teleworkable job, increasing the likelihood by about 17 and 15 p.p., respectively. By contrast, marital status, having children in the household and having a migration background do not significantly affect the likelihood of having a teleworkable job; however, these factors drive the selection into actually working from home. With respect to workplace characteristics, having management responsibilities and using computers significantly increase both the chance of having a teleworkable job and actually working regularly from home. Finally, plant sizes appear not significantly correlated with WFH practice or potential, all else equal. Overall, the results confirm the findings of earlier studies, demonstrating that it is especially the better-educated, higher-skilled employees who have the possibility to work from home.

[30]Since this is a linear probability model, the coefficients on binary covariates can be interpreted as percentage-point changes in the probability of WFH when the dummy is switched on.

Table A6: Worker-Level Correlations between WFH and Worker Characteristics

| | *WFH freq* | | | *WFH feas* | | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Female | | -0.003 | -0.007 | | 0.013 | 0.008 |
| | | (0.008) | (0.008) | | (0.011) | (0.011) |
| Age | | 0.001*** | 0.001*** | | -0.002*** | -0.002*** |
| | | (0.000) | (0.000) | | (0.000) | (0.000) |
| University degree | | 0.077*** | 0.077*** | | 0.178*** | 0.173*** |
| | | (0.009) | (0.009) | | (0.011) | (0.011) |
| Migrant | | -0.025*** | -0.025*** | | -0.021 | -0.024 |
| | | (0.009) | (0.009) | | (0.015) | (0.015) |
| Married | | 0.019*** | 0.019*** | | 0.007 | 0.008 |
| | | (0.007) | (0.007) | | (0.011) | (0.011) |
| Children in the household | | 0.025*** | 0.024*** | | 0.019* | 0.017 |
| | | (0.007) | (0.007) | | (0.011) | (0.011) |
| Contractual working hours | | 0.001 | 0.000 | | 0.001 | 0.001 |
| | | (0.000) | (0.000) | | (0.001) | (0.001) |
| Manager | | 0.036*** | 0.036*** | | 0.075*** | 0.077*** |
| | | (0.007) | (0.007) | | (0.011) | (0.011) |
| PC usage | | 0.046*** | 0.045*** | | 0.155*** | 0.148*** |
| | | (0.006) | (0.006) | | (0.018) | (0.018) |
| Plant size | | | | | | |
| 50-249 employees | | -0.002 | 0.001 | | -0.004 | -0.006 |
| | | (0.007) | (0.007) | | (0.012) | (0.013) |
| 250+ employees | | -0.011 | -0.006 | | -0.002 | -0.003 |
| | | (0.007) | (0.007) | | (0.012) | (0.012) |
| $R^2$ | 0.21 | 0.23 | 0.24 | 0.27 | 0.31 | 0.31 |
| Employees | 17,130 | 16,065 | 15,938 | 17,112 | 16,046 | 15,920 |
| Occupation F.E. | × | × | × | × | × | × |
| Sector F.E. | | | × | | | × |

*Notes:* The dependent variable in Columns (1) - (3) is a binary variable identifying employees who report working from home "frequently" or "always" (*WFH freq*). The dependent variable in Columns (4) - (6) is an indicator identifying workers who ever work from home or who do not exclude the possibility of doing so, provided the employer grants the option (*WFH feas*). Migrant, Children and Manager take the value 1 for employees with migration background, children below the age of 13 living in the household, or with personnel responsibility, respectively. PC usage and academic degree are 1 for respondents who use a PC for work or who hold a university degree, respectively. The reference category of plant size is plant size of 1-49 employees. Occupation fixed effects include 37 categories at the 2-digit KldB level. Sector fixed effects include 21 NACE rev.2 categories. Regressions use population weights. Robust standard errors reported in parentheses. Data are from the BIBB/BAuA Employment Survey 2018. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

## A.4 Robustness: Effect of WFH on Realized Short-Time Work at the County Level

This section provides robustness checks for the effect of WFH on short-time work at the regional level, presented in Section 2.2. In particular, we proxy regional labor market shocks with the share of *realized* STW claims instead of STW *applications* as in the main body of the paper. The Federal Employment Agency (BA) publishes data on realized short-time work with a lag of several months due to the approval and reimbursement process ensuing companies' notification at the local agency. As data on realized STW is available for the period before the onset of the COVID-19 pandemic in Germany, one can assess the differential effect of WFH on short-time work claims over time. It should be noted though that while the short-time-work scheme existed already before the COVID-19 crisis, the scheme was greatly expanded in March 2020 and the eligibility criteria were relaxed. As a result of these changes to the institutional framework, the comparison of effects before and during the pandemic should be interpreted with a degree of caution.

We first replicate the regression of Section 2.2 using realized STW claims for March and April 2020. The dependent variable is the percentage share of realized short-time work relative to local employment in June 2019. We use the same sets of control variables introduced in Section 2.2. The results presented in Table A7 confirm that also realized STW claims are significantly negatively related to the regional WFH share. The effect size estimates of WFH are slightly larger for realized STW, suggesting that measuring adjustments in the labor market with STW applications underestimates spill-over effects from WFH.

Next, we present placebo regressions for the effect of WFH on realized short-time work in January 2020. Since the possibility to WFH before the pandemic should be unrelated to the degree of local labor market shocks, we expect a negligible association between WFH and STW in January. The results in Table A8 confirm this intuition. They show that our 3 measures for WFH are very weakly correlated with STW in January and the point estimates are several orders of magnitude smaller than in March and April. Controlling for the full set of covariates (Column 5) renders the effect size statistically indistinguishable from zero, supporting the hypothesis that the mitigating effect of WFH is specific to the pandemic crisis.[31]

Finally, we assess the differential effect of WFH on realized STW over the first five months of the year 2020. The dependent variable $STW_{im}$ is the inflow of STW claims normalized with total employment in June 2019 in county $i$ in month $m$. We estimate:

$$STW_{im} = \sum_{m=1}^{5} \delta_m WFH_i \times m + \gamma_i + \gamma_m + \epsilon_{im}, \tag{7}$$

where $\gamma_i$ and $\gamma_m$ are county and month fixed effects, respectively. Figure A3 displays the OLS estimates of $\delta_{im}$, which capture the month-specific effect of *WFH freq* on STW inflows, taking

[31] Using STW claims in February 2020 instead of January yields very similar results.

January as the reference month. The estimates confirm the crisis-mitigating effect of WFH during the first wave of the pandemic. The null hypothesis that the WFH effect on STW in March, April and May is identical to the one in February can be clearly rejected ($F = 18.49$, $p < 0.01$).

Table A7: Robustness: Effect of WFH and Realized STW in March/April 2020

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *WFH feas* | -1.22*** | -1.01*** | -1.38*** | -1.39*** | -1.21*** |
| | (0.25) | (0.22) | (0.25) | (0.27) | (0.25) |
| $R^2$ | 0.22 | 0.23 | 0.30 | 0.25 | 0.34 |
| NUTS-3 regions | 401 | 399 | 391 | 401 | 389 |
| *WFH occ* | -1.65*** | -1.57*** | -1.89*** | -2.11*** | -2.02*** |
| | (0.27) | (0.24) | (0.28) | (0.31) | (0.29) |
| $R^2$ | 0.25 | 0.27 | 0.33 | 0.30 | 0.38 |
| NUTS-3 regions | 401 | 399 | 391 | 401 | 389 |
| *WFH freq* | -3.11*** | -3.20*** | -3.56*** | -4.37*** | -4.18*** |
| | (0.53) | (0.46) | (0.57) | (0.62) | (0.55) |
| $R^2$ | 0.24 | 0.26 | 0.30 | 0.30 | 0.37 |
| NUTS-3 regions | 401 | 399 | 391 | 401 | 389 |
| **Set of Controls** | | | | | |
| Baseline | × | × | × | × | × |
| Economy | | × | | | × |
| Health | | | × | | × |
| Social Capital | | | | × | × |

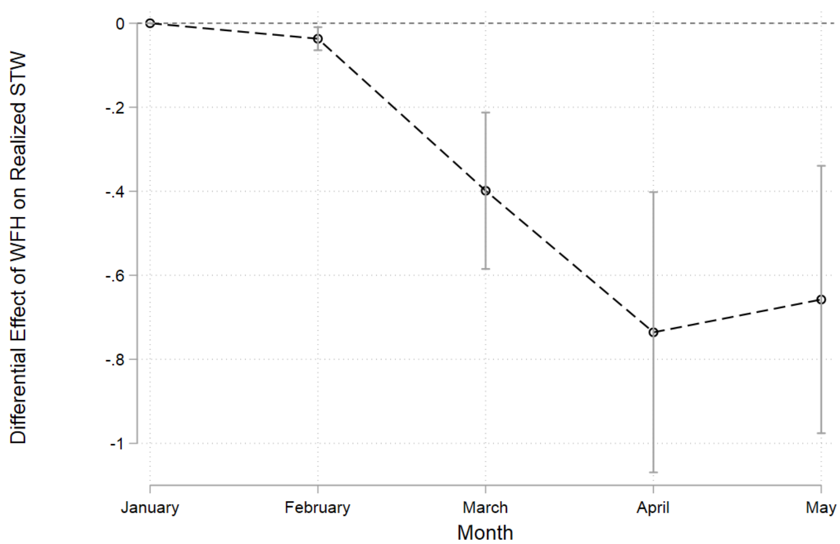
*Notes:* Dependent variable is the percentage of the realized short-time work claims in March and April 2020 relative to employment in June 2019 based on data from the Federal Employment Agency. WFH is the percentage share of employees in the county with jobs that are suitable for telework (*WFH feas*) 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* control variables are 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 ($\geq$ 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 ($\geq$ 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A8: Robustness: Effect of WFH and Realized STW in January 2020

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *WFH feas* | -0.03* | 0.01 | -0.02 | -0.02 | 0.02 |
| | (0.01) | (0.02) | (0.01) | (0.02) | (0.02) |
| $R^2$ | 0.08 | 0.20 | 0.10 | 0.11 | 0.25 |
| NUTS-3 regions | 401 | 399 | 391 | 401 | 389 |
| *WFH occ* | -0.04** | 0.01 | -0.03 | -0.03 | 0.03 |
| | (0.02) | (0.02) | (0.02) | (0.02) | (0.02) |
| $R^2$ | 0.08 | 0.20 | 0.10 | 0.11 | 0.25 |
| NUTS-3 regions | 401 | 399 | 391 | 401 | 389 |
| *WFH freq* | -0.09*** | -0.01 | -0.08** | -0.10** | 0.03 |
| | (0.03) | (0.03) | (0.03) | (0.04) | (0.04) |
| $R^2$ | 0.09 | 0.20 | 0.11 | 0.12 | 0.25 |
| NUTS-3 regions | 401 | 399 | 391 | 401 | 389 |
| **Set of Controls** | | | | | |
| Baseline | × | × | × | × | × |
| Economy | | × | | | × |
| Health | | | × | | × |
| Social Capital | | | | × | × |

*Notes:* Dependent variable is the percentage of the realized short-time work claims in January 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 ($\geq$ 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 ($\geq$ 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure A3: Robustness: The Effect of Working from Home on Realized Short-Time Work over Time




*Notes:* The Figure plots coefficient estimates of $WFH_i \times m$ (using *WFH freq*, the percentage share of employees in the county with jobs that frequently do telework) on realized short-time work claims relative to June 2019 employment by month. The reference month is January 2020. Standard errors are clustered at the county level. 95-percent confidence intervals are reported.

## A.5 Firm-Level Adoption of WFH During the COVID-19 Crisis and Firm-Level Robustness Accounting for Demand Shocks

In this section, we first present a validation exercise, showing that our WFH measures perform well in predicting firm-level teleworking patterns in April 2020. Second, we show that our analysis of the impact of WFH on firm distress presented in Section 2.3 is robust to accounting for self-reported demand contraction due to the pandemic.

**Validation of WFH measures:** Table A9 reports the coefficients from regressing the firm-level indicator identifying firms who reported intensified telework on our industry-level WFH measures. Our control variables are identical to the ones discusses in Section 2.3, in particular, controls include firm size, firms' export share, survey fixed effects and fixed effects for the survey completion date (Baseline controls). Additional controls (even columns) include an indicator for firms operating in an industry subject to mandatory business closure as well as self-reported business conditions and business expectations in Q4 2019. All specifications include location fixed effects at the county level.

Columns (1), (3) and (5) show that a higher industry share of WFH measured by any of our proxies is associated with a statistically significant increase in the probability to expand telework during the crisis. In terms of magnitudes, increasing *WFH feas* by one p.p. increases the probability that a firm intensifies telework during the COVID-19 crisis by 0.9 p.p. The effects for *WFH occ* (1.45) and *WFH freq* (3 p.p.) are even larger. This is in line with the view that industries with higher WFH rates before the crisis could more easily switch to telework during the pandemic. The coefficient magnitudes are slightly reduced and remain highly significant when adding more covariates in Columns (2), (4) and (6). The effect of a mandatory business closure is strongly negative as firms in the accommodation, restaurant and retail trade sectors did not rely much on telework. Finally, firms reporting an unfavorable state of business before the crisis are slightly less likely to take up telework relative to firms in a neutral state. Overall, the results show that our measures perform well in predicting firms' teleworking patterns during the crisis.

**Robustness to demand shock:** Table A10 replicates Table 2 additionally controlling for self-reported contraction of demand due to the COVID-19 crisis for the subsample of sectors for which the information is available (Wholesale/Retail, Service, Manufacturing). Specifically, *Demand Drop (Industry)* is the leave-one-out (employment weighted) industry average of firms reporting a demand drop within a 2-digit industry. A contraction in demand by one p.p. increases the probability of filing for STW (reporting an adverse COVID-19 impact) by 22 to 24 p.p. (20 p.p.). The effects are significant at the five and ten percent level, respectively. The impact of controlling for demand on our estimate of interest only changes slightly: compared to the IV-estimates in Table 2, the estimates for the effect of relying on telework during the crises change from -49.42 to -52.65 (Panel A) and -39.13 to -40.14 (Panel B). Since businesses that were subjected to mandatory business closures experienced the most severe demand contraction, it is likely that our indicator for mandatory shutdowns already absorbs a lot of the demand effect. Overall, our results prove robust to demand-side shocks during the crisis.

Table A9: Intensified Telework Due to COVID-19 and WFH Potential – Firm-Level Evidence

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **WFH feas** | 1.14*** | 0.92*** | | | | |
| | (0.16) | (0.10) | | | | |
| **WFH occ** | | | 1.45*** | 1.15*** | | |
| | | | (0.27) | (0.20) | | |
| **WFH freq** | | | | | 3.01*** | 2.43*** |
| | | | | | (0.51) | (0.25) |
| **Mandatory shutdown** | | -18.10*** | | -20.78*** | | -26.14*** |
| | | (6.65) | | (7.56) | | (9.25) |
| **State of Business 2019Q4** | | | | | | |
| negative | | -2.61* | | -2.84* | | -2.97* |
| | | (1.54) | | (1.52) | | (1.50) |
| positive | | 0.30 | | 0.47 | | 1.05 |
| | | (1.48) | | (1.59) | | (1.72) |
| $R^2$ | 0.33 | 0.34 | 0.32 | 0.34 | 0.29 | 0.33 |
| Firms | 6,028 | 5,796 | 6,028 | 5,796 | 6,028 | 5,796 |
| Baseline | × | × | × | × | × | × |
| Controls | | × | | × | | × |

*Notes:* The dependent variable is an indicator (rescaled by 100) identifying firms who report an having intensified telework in response to the COVID-19 crisis in April 2020. WFH is of the percentage share of employees in the NACE-2 industry 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. 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A10: Robustness: Accounting for Demand Shock: Effect of WFH on STW and COVID-19 Shock

| | RF | | OLS | | IV | |
|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) |
| *Panel A: Participated in Short-Time Work Scheme* | | | | | | |
| **Intensified Telework** | | | -14.66*** | -6.13*** | -72.09*** | -52.65*** |
| | | | (3.94) | (1.64) | (11.16) | (12.95) |
| **WFH feas** | -0.82*** | -0.46*** | | | | |
| | (0.20) | (0.12) | | | | |
| **Mandatory shutdown** | | 27.93*** | | 32.89*** | | 18.35*** |
| | | (4.86) | | (5.07) | | (6.33) |
| **State of Business 2019Q4** | | | | | | |
| negative | | 12.71*** | | 12.79*** | | 11.49*** |
| | | (1.64) | | (1.73) | | (1.95) |
| positive | | -10.47*** | | -10.94*** | | -9.80*** |
| | | (2.24) | | (2.36) | | (2.19) |
| **Demand Drop (Industry)** | | 22.94** | | 23.67** | | 22.05** |
| | | (8.83) | | (9.61) | | (8.68) |
| $R^2$ | 0.16 | 0.22 | 0.13 | 0.21 | | |
| Firms | 5,337 | 4,687 | 5,337 | 4,687 | 5,337 | 4,687 |
| First stage estimate (×100) | | | | | 1.14*** | 0.88*** |
| First stage KP F stat | | | | | 50.71 | 74.46 |
| *Panel B: Negative Corona Shock* | | | | | | |
| **Intensified Telework** | | | -16.57*** | -7.25** | -75.18*** | -40.14*** |
| | | | (5.35) | (2.73) | (14.50) | (12.60) |
| **WFH feas** | -0.86*** | -0.36*** | | | | |
| | (0.25) | (0.12) | | | | |
| **Mandatory shutdown** | | 39.46*** | | 42.56*** | | 32.52*** |
| | | (6.06) | | (6.27) | | (5.68) |
| **State of Business 2019Q4** | | | | | | |
| negative | | 10.39*** | | 10.36*** | | 9.25*** |
| | | (2.54) | | (2.66) | | (3.03) |
| positive | | -10.26*** | | -10.62*** | | -10.03*** |
| | | (2.19) | | (2.22) | | (2.13) |
| **Demand Drop (Industry)** | | 19.59* | | 20.09* | | 19.18* |
| | | (10.33) | | (10.88) | | (10.18) |
| $R^2$ | 0.16 | 0.26 | 0.13 | 0.25 | | |
| Firms | 4,731 | 4,147 | 4,731 | 4,147 | 4,731 | 4,147 |
| First stage estimate (×100) | | | | | 1.15*** | 0.90*** |
| First stage KP F stat | | | | | 52.21 | 78.03 |
| 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 (Wholesale/Retail, Service and Manufacturing) and location fixed effects at the county level. *Demand Drop (Industry)* is the leave-one-out (employment weighted) share of firms reporting a drop in demand due to the COVID-19 crisis in each 2-digit NACE industry. 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

## A.6 Details and Robustness: Working from Home and the Spread of COVID-19

This section presents additional results and robustness checks regarding the relation between the spread of SARS-CoV-2 and opportunities to work from home.

**Fatalities:** Table A11 considers fatality rates instead of infection rates as an outcome and replicates the specifications in Table 3. The coefficient of WFH is negative throughout all specifications and in most cases significant at the one-percent level. Compared to the coefficient estimates on infection rates, the coefficients on fatality rates are quantitatively larger.

**Poisson estimates:** Since there are several counties in our data that report zero COVID-19 fatalities, we report Poisson estimates using infections and fatalities as dependent variables, replicating the specifications in Tables 3 and A11. Results in Tables A12 and A13 imply a negative relation between WFH and infections or fatalities which is significant in all but one specification.

**Interactions with labor market characteristics:** In Table A14, we interact our measures of WFH with the fraction of the population in working age (Panel A) or the fraction of population in employment (Panel B). If our measure of WFH indeed captures reduced work-related interactions that prevent the spread of SARS-CoV-2 infections, we would expect larger effects of WFH in counties with *i.* a larger share of people in working age and *ii.* a larger share of people in employment. The results in Table A14 are consistent with this mechanism, as the interaction term is negative and significant in most specifications and the direct effect of WFH turns positive.

**Interactions with household incomes:** In Table A15, we interact WFH with the fraction of low-income households within the county (household income $\leq$ EUR 1,500 per month, Panel A) and with the fraction of high-income households within the county (household income $\geq$ EUR 3,600 per month, Panel B). We find health benefits of WFH to be stronger in more affluent counties and weaker in less affluent counties.

**Spillover effects from commuting:** In Table A16, we study spillover effects from commuting. Potentially, health benefits of WFH can spill over across counties when residents have their workplaces in adjacent counties. We address this using data from the German *Pendleratlas* that provides a matrix of commuting flows across county pairs. Using this data and based on the 30 closest counties, we calculate the log number of inward and outward commuters for each county. Furthermore, we calculate a place-of-residence-based WFH measure and WFH averages for the adjacent counties that are either residence- or workplace-based. Panel A of Table A16 studies spillovers from inward commuting. Besides the usual local health benefits of WFH, we find positive spillover effects of WFH from commuters for the counties where they live. Similarly to the local WFH effects, spillover effects of WFH appear significant at the one-percent level. Panel B instead considers spillover effects from outward commuting and finds similar spillover effects for counties where commuters work that also appear to be significant at the one-percent level.

**Infection-reducing effect of WFH over time:** We estimate a simple difference-in-differences specification in which we regress weekly county-level infection rates on an interaction of our WFH measures with a *pre confinement* dummy that indicates weeks before the confinement (weeks 1-7) including week and county fixed effects. In line with the weekly estimates reported in Figure 1, the results in Table A17 imply that infection-reducing effects of WFH were largest before the confinement suggesting a substitutive relationship between confinement and WFH.

**Interaction with confinement strictness:** In Figure A4, we replicate the estimates shown in Figure 1 but split our sample into two subsamples to show further robustness on the claim that there is no complementarity between WFH and confinement strictness. During the first wave of the COVID-19 pandemic 6 of the 16 German states opted for a more strict confinement (*Ausgangsbeschränkungen*, see Appendix A.2). However, we find very similar dynamic health benefits of WFH for both samples.

**Using infection data from later dates after the first wave of the COVID-19 pandemic:** In all our analyses, we focused on infection data from the first wave of the pandemic for the benefit of a cleaner empirical setting. Here, we report estimates for later dates (July 29 and September 30). After the first confinement period ended in the beginning of May, there was substantial regional heterogeneity in post-confinement social distancing rules. Moreover, the timing of summer holidays, when few people worked and a large share of the population traveled, varies substantially across German states. These factors make it harder to identify the impact of WFH at the region level during the summer. However, our results are robust: Tables A18 and A19 imply that the negative relation between WFH and infections still holds.

Table A11: Robustness: The Effect of WFH on SARS-CoV-2 Fatalities across Counties

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *WFH feas* | -0.088*** | -0.086*** | -0.088*** | -0.089*** | -0.086*** |
| | (0.023) | (0.027) | (0.024) | (0.025) | (0.031) |
| $R^2$ | 0.27 | 0.31 | 0.29 | 0.31 | 0.34 |
| NUTS-3 regions | 369 | 367 | 362 | 369 | 360 |
| *WFH occ* | -0.12*** | -0.11*** | -0.11*** | -0.12*** | -0.11*** |
| | (0.029) | (0.033) | (0.031) | (0.032) | (0.040) |
| $R^2$ | 0.28 | 0.31 | 0.29 | 0.31 | 0.33 |
| NUTS-3 regions | 369 | 367 | 362 | 369 | 360 |
| *WFH freq* | -0.23*** | -0.18** | -0.20*** | -0.21*** | -0.13 |
| | (0.067) | (0.081) | (0.073) | (0.076) | (0.097) |
| $R^2$ | 0.28 | 0.30 | 0.29 | 0.30 | 0.33 |
| NUTS-3 regions | 369 | 367 | 362 | 369 | 360 |
| **Set of Controls** | | | | | |
| Baseline | × | × | × | × | × |
| Economy | | × | | | × |
| Health | | | × | | × |
| Social Capital | | | | × | × |

*Notes:* Dependent variable is the SARS-CoV-2 fatality rate (in logs) up to May 06, 2020 (the end date of the first confinement period) based on data from the Robert-Koch-Institut. WFH is of 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 ($\geq$ 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 ($\geq$ 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A12: Robustness: The Effect of Working from Home on SARS-CoV-2 Infections across Counties – Poisson Estimates

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *WFH feas* | -0.051*** | -0.058*** | -0.045*** | -0.052*** | -0.048*** |
| | (0.015) | (0.017) | (0.015) | (0.015) | (0.018) |
| $R^2$ | 0.88 | 0.89 | 0.90 | 0.90 | 0.92 |
| NUTS-3 regions | 401 | 399 | 391 | 401 | 389 |
| *WFH occ* | -0.065*** | -0.071*** | -0.057*** | -0.066*** | -0.068*** |
| | (0.018) | (0.021) | (0.019) | (0.020) | (0.023) |
| $R^2$ | 0.88 | 0.90 | 0.90 | 0.90 | 0.92 |
| NUTS-3 regions | 401 | 399 | 391 | 401 | 389 |
| *WFH freq* | -0.12*** | -0.12** | -0.11*** | -0.12** | -0.11** |
| | (0.040) | (0.051) | (0.039) | (0.045) | (0.055) |
| $R^2$ | 0.88 | 0.89 | 0.90 | 0.90 | 0.92 |
| NUTS-3 regions | 401 | 399 | 391 | 401 | 389 |
| **Set of Controls** | | | | | |
| Baseline | × | × | × | × | × |
| Economy | | × | | | × |
| Health | | | × | | × |
| Social Capital | | | | × | × |

*Notes:* Dependent variable is the number of SARS-CoV-2 infections up to May 06, 2020 (the end date of the first confinement) based on data from the Robert-Koch-Institut. WFH is of 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 ($\geq$ 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 ($\geq$ 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A13: Robustness: The Effect of Working from Home on SARS-CoV-2 Fatalities across Counties – Poisson Estimates

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *WFH feas* | -0.11*** | -0.097*** | -0.10*** | -0.11*** | -0.089*** |
| | (0.023) | (0.027) | (0.027) | (0.026) | (0.032) |
| $R^2$ | 0.54 | 0.58 | 0.59 | 0.58 | 0.67 |
| NUTS-3 regions | 401 | 399 | 391 | 401 | 389 |
| *WFH occ* | -0.13*** | -0.11*** | -0.12*** | -0.13*** | -0.11** |
| | (0.029) | (0.036) | (0.032) | (0.034) | (0.042) |
| $R^2$ | 0.55 | 0.58 | 0.59 | 0.58 | 0.67 |
| NUTS-3 regions | 401 | 399 | 391 | 401 | 389 |
| *WFH freq* | -0.24*** | -0.17* | -0.20*** | -0.23*** | -0.11 |
| | (0.067) | (0.088) | (0.070) | (0.078) | (0.10) |
| $R^2$ | 0.54 | 0.58 | 0.59 | 0.57 | 0.67 |
| NUTS-3 regions | 401 | 399 | 391 | 401 | 389 |
| **Set of Controls** | | | | | |
| Baseline | × | × | × | × | × |
| Economy | | × | | | × |
| Health | | | × | | × |
| Social Capital | | | | × | × |

*Notes:* Dependent variable is the number of SARS-CoV-2 fatalities up to May 06, 2020 (the end date of the first confinement) based on data from the Robert-Koch-Institut. WFH is of 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 ($\geq$ 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 ($\geq$ 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A14: Robustness: The Effect of WFH on SARS-CoV-2 Infections across Counties - Labor Market Interactions

| | (1) | (2) | (3) |
|---|---|---|---|
| **WFH measure** | *WFH feas* | *WFH occ* | *WFH freq* |
| **Panel A:** | *Working Age Population Share (%)* | | |
| WFH x Working age | -0.0047*** | -0.0056** | -0.0079 |
| | (0.0016) | (0.0023) | (0.0062) |
| WFH | 0.28** | 0.32** | 0.43 |
| | (0.11) | (0.16) | (0.43) |
| Working age | 0.30*** | 0.18*** | 0.12** |
| | (0.087) | (0.059) | (0.060) |
| $R^2$ | 0.57 | 0.57 | 0.57 |
| NUTS-3 regions | 401 | 401 | 401 |
| **Panel B:** | *Employment Share (%)* | | |
| WFH x Employment | -0.0045*** | -0.0058*** | -0.014*** |
| | (0.0012) | (0.0017) | (0.0041) |
| WFH | 0.14*** | 0.18** | 0.43** |
| | (0.052) | (0.072) | (0.17) |
| Employment | 0.26*** | 0.16*** | 0.13*** |
| | (0.068) | (0.044) | (0.038) |
| $R^2$ | 0.56 | 0.56 | 0.56 |
| NUTS-3 regions | 401 | 401 | 401 |
| Baseline controls | × | × | × |

*Notes:* Dependent variable is the SARS-CoV-2 infection rate (in logs) up to May 06, 2020 (the end date of the first confinement) based on data from the Robert-Koch-Institut. WFH is of 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. Panel A includes interactions with the regional percentage share of working age population and Panel B includes interactions with regional percentage employment shares. *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. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A15: Robustness: The Effect of WFH on SARS-CoV-2 Infections across Counties - Income Group Interactions

| | (1) | (2) | (3) |
|---|---|---|---|
| **WFH measure** | *WFH feas* | *WFH occ* | *WFH freq* |
| **Panel A:** | *Share of Low-Income Households (%)* | | |
| WFH x share low income | 0.0028*** | 0.0034*** | 0.0068*** |
| | (0.00065) | (0.00095) | (0.0025) |
| WFH | -0.12*** | -0.14*** | -0.29*** |
| | (0.018) | (0.025) | (0.072) |
| share low income | -0.17*** | -0.11*** | -0.081*** |
| | (0.037) | (0.025) | (0.024) |
| $R^2$ | 0.59 | 0.59 | 0.58 |
| NUTS-3 regions | 401 | 401 | 401 |
| **Panel B:** | *Share of High-Income Households (%)* | | |
| WFH x share high income | -0.0028*** | -0.0033*** | -0.0069*** |
| | (0.00070) | (0.00100) | (0.0026) |
| WFH | 0.021 | 0.021 | 0.047 |
| | (0.022) | (0.030) | (0.072) |
| share high income | 0.18*** | 0.10*** | 0.079*** |
| | (0.041) | (0.028) | (0.027) |
| $R^2$ | 0.58 | 0.57 | 0.56 |
| NUTS-3 regions | 401 | 401 | 401 |
| Baseline controls | × | × | × |

*Notes:* Dependent variable is the SARS-CoV-2 infection rate (in logs) up to May 06, 2020 (the end date of the first confinement) based on data from the Robert-Koch-Institut. WFH is of 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. Panel A includes interactions with the regional percentage share of low-income households ($\leq$ EUR 1,500 per month) and Panel B includes interactions with the regional percentage share of high-income households ($\geq$ EUR 3,600 per month). *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. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A16: Robustness: The Effect of WFH on SARS-CoV-2 Infections across Counties - Regional Spillovers from Commuting

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| **WFH measure** | *WFH feas* | | *WFH occ* | | *WFH freq* | |
| **Panel A:** | *Spillovers from Inward Commuters* | | | | | |
| WFH | -0.046*** | -0.040*** | -0.061*** | -0.053*** | -0.11*** | -0.11*** |
| | (0.010) | (0.010) | (0.013) | (0.013) | (0.028) | (0.028) |
| Commuters | 0.043 | 2.18*** | 0.065 | 1.46*** | 0.087 | 1.25*** |
| | (0.071) | (0.52) | (0.071) | (0.34) | (0.071) | (0.32) |
| WFH (adjacent) | 0.0027 | 0.41*** | -0.021 | 0.56*** | -0.14** | 1.21*** |
| | (0.017) | (0.091) | (0.023) | (0.13) | (0.054) | (0.36) |
| WFH (adjacent) x Commuters | | -0.039*** | | -0.056*** | | -0.13*** |
| | | (0.0092) | | (0.013) | | (0.035) |
| $R^2$ | 0.65 | 0.66 | 0.65 | 0.67 | 0.65 | 0.66 |
| NUTS-3 regions | 401 | 401 | 401 | 401 | 401 | 401 |
| **Panel B:** | *Spillovers from Outward Commuters* | | | | | |
| WFH | -0.016* | -0.016* | -0.035*** | -0.034*** | -0.080*** | -0.080*** |
| | (0.0094) | (0.0092) | (0.012) | (0.012) | (0.026) | (0.026) |
| Commuters | 0.065 | 4.51*** | 0.12* | 2.76*** | 0.13** | 1.80*** |
| | (0.076) | (0.77) | (0.072) | (0.50) | (0.066) | (0.51) |
| WFH (adjacent) | -0.017 | 0.85*** | -0.060** | 1.08*** | -0.24*** | 1.74*** |
| | (0.020) | (0.14) | (0.027) | (0.21) | (0.062) | (0.59) |
| WFH (adjacent) x Commuters | | -0.083*** | | -0.11*** | | -0.19*** |
| | | (0.014) | | (0.020) | | (0.057) |
| $R^2$ | 0.63 | 0.66 | 0.64 | 0.66 | 0.65 | 0.66 |
| NUTS-3 regions | 401 | 401 | 401 | 401 | 401 | 401 |
| Baseline | × | × | × | × | × | × |

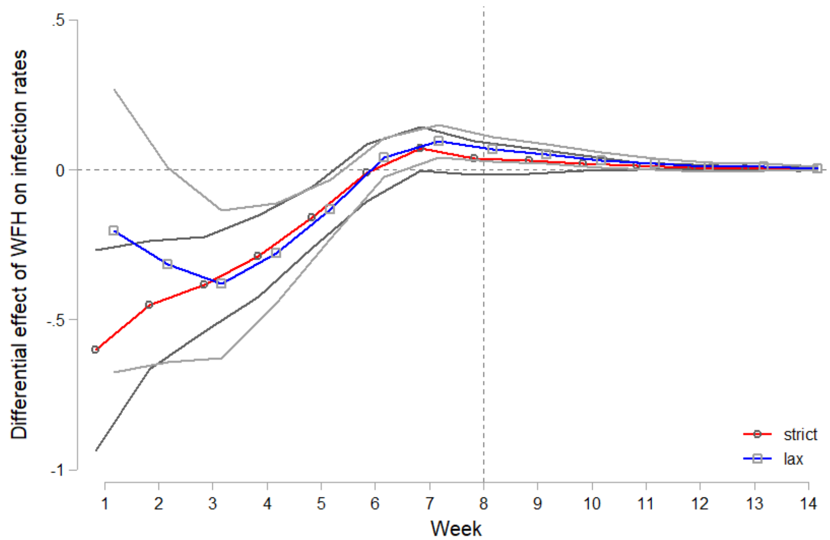
*Notes:* Dependent variable is the SARS-CoV-2 infection rate (in logs) up to May 06, 2020 (the end date of the first confinement) based on data from the Robert-Koch-Institut. WFH is of the percentage share of employees (Panel A) or residents (Panel B) in the county with jobs that are suitable for telework (*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. Panel A includes the following variables based on the 30 most adjacent counties: the log number of inward commuters from these counties, WFH (residence-weighted) and their interaction. Panel B includes the following variables based on the 30 most adjacent counties: the log number of outward commuters to these counties, WFH (workplace-weighted) and their interaction. *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. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A17: The Spread of SARS-CoV-2 Pre- and Post-Confinement and Working from Home

| | (1) | (2) | (3) |
|---|---|---|---|
| **WFH measure** | *WFH feas* | *WFH occ* | *WFH freq* |
| WFH × Pre confinement | -0.018** | -0.026** | -0.053** |
| | (0.0077) | (0.010) | (0.023) |
| $R^2$ | 0.96 | 0.96 | 0.96 |
| Observations | 4,270 | 4,270 | 4,270 |
| County F.E. | × | × | × |
| Week F.E. | × | × | × |

*Notes:* Dependent variable is the weekly SARS-CoV-2 infection rate (in logs) at the NUTS-3 level based on data from the Robert-Koch-Institut. WFH is of 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. *Pre confinement* is a dummy variable that indicates weeks 1-7. Observations correspond to individual weeks within NUTS-3 regions (counties). Controls are region-specific weakly rainfall and log weekly spatial infection rates defined as a weighted mean of infection rates in other counties using inverse distances as weights. Standard errors are corrected for clustering at the NUTS-3 county level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure A4: Robustness: The Effect of WFH on SARS-CoV-2 Infections by Confinement Strictness 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) for two subsamples (*lax* and *strict*). Subsample *lax* contains counties from 10 states with more lax confinement rules (*Kontaktbeschränkungen*), subsample *strict* contains counties from 6 states with stricter confinement rules (*Ausgangsbeschränkungen*). 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).

Table A18: Robustness: The Effect of WFH on SARS-CoV-2 Infections across Counties - Other Weeks

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | July 29, 2020 | | | | | September 30, 2020 | | | | |
| *WFH feas* | -0.050*** | -0.051*** | -0.048*** | -0.053*** | -0.046*** | -0.045*** | -0.045*** | -0.042*** | -0.046*** | -0.035*** |
| | (0.012) | (0.014) | (0.012) | (0.011) | (0.014) | (0.0097) | (0.012) | (0.0096) | (0.0088) | (0.011) |
| $R^2$ | 0.55 | 0.60 | 0.59 | 0.61 | 0.64 | 0.65 | 0.68 | 0.69 | 0.70 | 0.73 |
| NUTS-3 regions | 401 | 399 | 391 | 401 | 389 | 401 | 399 | 391 | 401 | 389 |
| *WFH occ* | -0.066*** | -0.063*** | -0.062*** | -0.068*** | -0.060*** | -0.060*** | -0.057*** | -0.054*** | -0.060*** | -0.046*** |
| | (0.014) | (0.017) | (0.015) | (0.013) | (0.017) | (0.012) | (0.015) | (0.012) | (0.011) | (0.014) |
| $R^2$ | 0.55 | 0.60 | 0.59 | 0.61 | 0.64 | 0.65 | 0.68 | 0.69 | 0.70 | 0.73 |
| NUTS-3 regions | 401 | 399 | 391 | 401 | 389 | 401 | 399 | 391 | 401 | 389 |
| *WFH freq* | -0.12*** | -0.087** | -0.11*** | -0.11*** | -0.071* | -0.11*** | -0.085** | -0.098*** | -0.100*** | -0.061* |
| | (0.033) | (0.039) | (0.034) | (0.033) | (0.043) | (0.028) | (0.034) | (0.028) | (0.028) | (0.034) |
| $R^2$ | 0.55 | 0.59 | 0.58 | 0.60 | 0.63 | 0.65 | 0.67 | 0.69 | 0.69 | 0.72 |
| NUTS-3 regions | 401 | 399 | 391 | 401 | 389 | 401 | 399 | 391 | 401 | 389 |
| **Set of Controls** | | | | | | | | | | |
| Baseline | × | × | × | × | × | × | × | × | × | × |
| Infrastructure | | × | | | × | | × | | | × |
| Health | | | × | | × | | | × | | × |
| Social Capital | | | | × | × | | | | × | × |

*Notes:* Dependent variables are the SARS-CoV-2 infection rates (in logs) up to July 29 or September 30, 2020 at the NUTS-3 level based on data from the Robert-Koch-Institut. WFH is of 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 ($\geq$ 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 ($\geq$ 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A19: Robustness: The Effect of WFH on SARS-CoV-2 Fatalities across Counties - Other Weeks

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) |
|---|---|---|---|---|---|---|---|---|---|---|
| | | | July 29, 2020 | | | | | September 30, 2020 | | |
| *WFH feas* | -0.073*** | -0.062** | -0.072*** | -0.074*** | -0.068** | -0.080*** | -0.076*** | -0.073*** | -0.074*** | -0.068** |
| | (0.021) | (0.025) | (0.022) | (0.022) | (0.026) | (0.022) | (0.026) | (0.023) | (0.023) | (0.028) |
| $R^2$ | 0.28 | 0.31 | 0.31 | 0.30 | 0.34 | 0.27 | 0.31 | 0.30 | 0.30 | 0.34 |
| NUTS-3 regions | 377 | 375 | 370 | 377 | 368 | 372 | 370 | 365 | 372 | 363 |
| *WFH occ* | -0.10*** | -0.089*** | -0.097*** | -0.10*** | -0.098*** | -0.11*** | -0.10*** | -0.097*** | -0.10*** | -0.090** |
| | (0.027) | (0.030) | (0.028) | (0.028) | (0.034) | (0.028) | (0.032) | (0.029) | (0.029) | (0.035) |
| $R^2$ | 0.29 | 0.32 | 0.31 | 0.31 | 0.35 | 0.28 | 0.31 | 0.30 | 0.31 | 0.34 |
| NUTS-3 regions | 377 | 375 | 370 | 377 | 368 | 372 | 370 | 365 | 372 | 363 |
| *WFH freq* | -0.20*** | -0.16** | -0.18*** | -0.20*** | -0.15* | -0.22*** | -0.18** | -0.18** | -0.19*** | -0.11 |
| | (0.064) | (0.074) | (0.068) | (0.066) | (0.083) | (0.067) | (0.079) | (0.070) | (0.070) | (0.088) |
| $R^2$ | 0.29 | 0.31 | 0.30 | 0.30 | 0.34 | 0.28 | 0.30 | 0.29 | 0.30 | 0.33 |
| NUTS-3 regions | 377 | 375 | 370 | 377 | 368 | 372 | 370 | 365 | 372 | 363 |
| **Set of Controls** | | | | | | | | | | |
| Baseline | × | × | × | × | × | × | × | × | × | × |
| Infrastructure | | × | | | × | | × | | | × |
| Health | | | × | | × | | | × | | × |
| Social Capital | | | | × | × | | | | × | × |

*Notes:* Dependent variables are the SARS-CoV-2 fatality rates (in logs) up to July 29 or September 30, 2020 at the NUTS-3 level based on data from the Robert-Koch-Institut. WFH is of 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 ($\geq$ 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 ($\geq$ 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

## A.7 A Dynamic Spatial Count Model of COVID-19 Infections

To show the robustness of our results regarding the impact of working from home on SARS-CoV-2 infections and its differential effect before the confinement period, in this Appendix we estimate a dynamic spatial count model of disease transmission, based on a standard modeling approach from the epidemiological literature (Höhle, 2015). The econometric model has been specifically designed for routine surveillance data, like those reported by RKI and does not require information about the number of susceptibles.[32]

This econometric model is significantly more flexible than the linear models we have used in the main body of the paper. We now use counts of *new* infections $Y_{it} = I_{it} - I_{it-1}$ in region $i$ in week $t$ as the dependent variable, which implies that unobserved county-specific effects affecting the level of infections are already differenced out. Moreover, instead of normalizing infections by regional population, we now use the latter as an explanatory variable, to allow for flexible interaction effects between them. We assume that $Y_{it}$ is drawn, alternatively, from a Poisson or negative Binomial (type-1) distribution with mean

$$\mu_{it} = e_i \nu_{it} + \lambda Y_{it-1} + \phi \sum_{j \neq i} w_{ij} Y_{jt-1}. \tag{8}$$

Here $e_i$ is the population share of region $i$, $\nu_{it}$ is the endemic mean of the process that depends on county-specific covariates, $\lambda Y_{it-1}$ captures the autoregressive (epidemic) component of infections and $\phi \sum_{j \neq i} w_{ij} Y_{jt-1}$ is the spatial component, capturing transmission from other counties. The spatial weights are modeled as power functions of distance, $w_{ij} = o_{ij}^{-d}$. Here $o_{ij}$ is the adjacency order of regions $i$ and $j$, corresponding to the number of regions that need to be crossed to get from $i$ to $j$, and $d$ is a spatial decay parameter to be estimated.[33]

The county-specific endemic component is modeled as the product of the county's population share $e_i$, accounting for regional exposure, and $\nu_{it}$, which is an exponential process including *WFH freq*, the interaction of *WFH freq* with a dummy for the pre-confinement period $Preconf_t$, a vector of county controls $\mathbf{Z}_{it}$, and a flexible time trend with a seasonal component:

$$\log \nu_{it} = \beta_0 WFH_i + \beta_1 WFH_i \times Preconf_t + \mathbf{Z_{it}}' \beta^{\nu} + \delta_t + \gamma_1 \sin \omega t + \gamma_2 \cos \omega t. \tag{9}$$

$\mathbf{Z}_{it}$ includes the set of baseline controls.

The results for this model are reported in Table A20. Columns (1) and (2) report coefficients for the Poisson model and Columns (3) and (4) for the negative Binomial model. The odd columns only include the direct impact of *WFH freq*, while the even columns additionally allow for a differential

[32] The formal inspiration for the model was the spatial branching process with immigration, which means that observation time and generation time have to correspond. For COVID-19 the generation time has been estimated to be roughly 5.5 days (Ganyani et al., 2020). In a series of successive papers the original modeling approach of Held et al. (2005) was subsequently extended such that it now constitutes a powerful and flexible regression approach for multivariate count data time series.

[33] We estimate the model using the R package `surveillance`, see (Meyer et al., 2017).

effect of *WFH freq* in the pre-confinement period. In all specifications, *WFH freq* has a negative effect on infection counts, which is significant at the one-percent level. Moreover, the interaction term $WFH_i \times \mathit{Preconf}_t$ is also negative and highly significant, confirming the additional infection-reducing impact of WFH before the confinement from the linear model.[34] The autoregressive coefficient $\lambda$ is quantitatively large and highly significant, indicating the importance of the epidemic component. Finally, the spatial component $\phi$ is also positive and significant, indicating that transmission from other regions plays a role. The AIC criterion suggests that the Negative Binomial model provides a better fit of the data than the Poisson model but the coefficient estimates are extremely similar across models.

Table A20: SARS-CoV-2 Infections and Working from Home: Dynamic Spatial Count Model

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| | *Infections* | | | |
| | *Poisson* | | *Negative Binomial* | |
| WFH | -0.1039*** | -0.0938*** | -0.1091*** | -0.0879*** |
| | (0.0076) | (0.0077) | (0.0245) | (0.0255) |
| WFH × Pre confinement | | -0.0334*** | | -0.0325*** |
| | | (0.0077) | | (0.0108) |
| $\lambda$ | 0.7101** | 0.7108*** | 0.6705*** | 0.6731*** |
| | (0.0046) | (0.0034) | (0.0142 | (0.0142) |
| $\phi$ | 0.0841*** | 0.0969*** | 0.1450*** | 0.1540*** |
| | (0.0026) | (0.0026) | (0.0075) | (0.0072) |
| Controls | × | × | × | × |
| log L | -29,279 | -29,222 | -15,956 | -15,952 |
| AIC | 58,578 | 58,466 | 31,935 | 31,928 |
| Obs. | 5,614 | 5,614 | 5,614 | 5,614 |
| NUTS-3 regions | 401 | 401 | 401 | 401 |

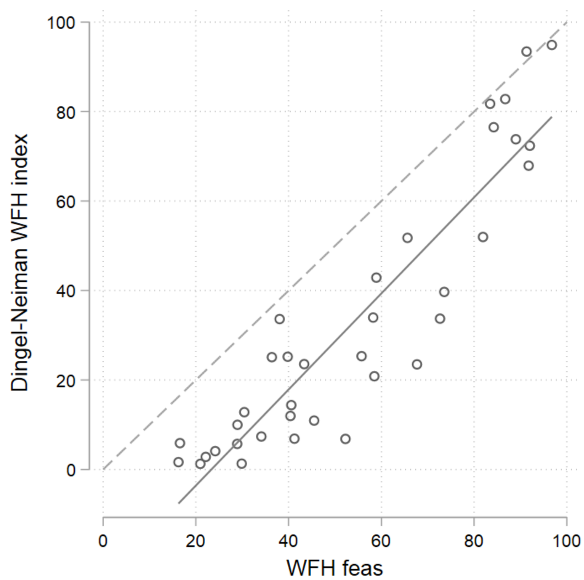
*Notes:* The Table reports estimated coefficients from a dynamic spatial epidemic count model. Dependent variable is the weekly number of SARS-CoV-2 infections at the NUTS-3 level based on data from the Robert-Koch-Institut. WFH is the percentage share of employees in the county with jobs that are frequently (*WFH freq*) doing telework. *Pre confinement* is a dummy variable that indicates weeks 1-7. Observations correspond to NUTS-3 regions (counties). Columns (1) and (2) report results from a Poisson model, Columns (3) and (4) from a Negative Binomial model (Type 1). Controls are population interacted with region-specific log settled area and log GDP. The spatial term includes the number of cases in other regions with estimated spatial weights.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

[34]Due to the non-linearity of the econometric model, only the signs of the coefficients allow for a straightforward interpretation, while the magnitudes of the coefficient estimates depend on the full set of covariates. In particular, the conditional expectation of the number of counts is given by $E(Y_{it}|X_{it}) = \mu_{it} = \exp(e_i\nu_{it} + \lambda Y_{it-1} + \phi \sum_{j \neq i} w_{ij} Y_{jt-1})$. Thus, the marginal effect of the WFH share (the expected change in the number of infections when increasing the WHS share by one unit) is given by $\frac{\partial E(Y_{it}|X_{it})}{\partial WFH_i} = (\beta_0 + \beta_1 \times \mathit{Preconf}_t)\nu_{it} e_i \mu_{it}$.

### A.8 Details and Robustness: Relation to Dingel and Neiman (2020)

To assess the robustness of our results with respect to the employed WFH measures, we replicate our analyses using the WFH feasibility index proposed by Dingel and Neiman (2020), hereafter DN. In their study, DN determine occupational tasks that are incompatible with working from home (e.g., working outdoors) based on US task information provided by O*NET- and classify occupations as either suitable or unsuitable for home-based work accordingly. We use their measures, which are published for download, and proceed in the same manner as described in Section 2.1 to compute WFH feasibility at the county and industry level. In the aggregate, 37% of German jobs are suitable for WFH according to the DN measure, a figure significantly lower than the estimated 56% WFH capacity estimated from the BIBB/BAuA Employment Survey. It is likely that the difference stems from DN's approach to measure the capacity for full-time WFH, whereas our WFH-feasibility measure includes also jobs suitable for part-time WFH. Discrepancies might also be explained by different task profiles of occupations in Germany compared to the US. Plotting DN's WFH index against our measure of overall WFH feasibility (*WFH feas*) at the 2-digit occupation level (Figure A5) shows that the two measures indeed differ mostly in terms of the level of WFH potential (occupations clustered below the dashed 45-degree line), while the correlation between the two measures is very high ($\rho = 0.92$). The correlation at the county-level is even higher ($\rho = 0.95$) as the measures are aggregated to regional WFH potential using identical occupation shares.

Figure A5: Correlation between *WFH feas* and Dingel-Neiman WFH index at the occupation level




*Notes:* The figure plots Dingel and Neiman's task-based WFH index against our survey-based measure of WFH feasibility (*WFH feas*) at the 2-digit occupation level (KldB 2010). The solid line reports the linear fit between the two measures ($R^2 = .84$). The dashed line highlights the 45-degree line.

**Robustness on STW using DN's measure of WFH:** First, we replicate the relationship between short-time work applications and WFH at the county level discussed in Section 2.2. Analogously to Table 1, which uses our WFH measures as key explanatory variables, Table A21 reports results from estimating the effect of WFH on the share of employees registered for STW in March and April 2020 using DN's WFH index. The estimates are always negative and significant at the one-percent level. In terms of magnitude, the coefficient estimates are closest to those using *WFH feas*.

**Robustness on STW using industry-level data and DN's measure of WFH:** Second, we show that the relationship between WFH and the share of employees registered for STW in March and April 2020 holds when estimated at the 2-digit industry-level instead of the county-level. Analogously to our county-level measures of WFH, industry-specific WFH is computed as a weighted sum over occupation-specific WFH-shares using industries' occupational composition obtained from the Federal Employment Agency (see Section 2.1 for details) as weights. Table A22 reports OLS results from estimating the effect of WFH on the share of STW for our three survey-based WFH measures and DN's task-based WFH index. The estimates are negative and significant at the one-percent level. Again, the coefficient associated with DN's WFH index is closest to the coefficient of *WFH feas*.

**Robustness on SARS-CoV-2 cases and fatalities using DN's measure of WFH:** Third, we replicate the relationship between the spread of SARS-CoV-2 and WFH at the county level discussed previously in Section 3. Table A23 reports estimates on infection rates and fatality rates using DN's WFH measure. The specifications are analogous to those from Tables 3 (for infections) and A11 (for fatalities). The estimates are negative and significant at the one- or the five-percent level across all specifications. Also in this case the coefficient estimates are quantitatively close to those using *WFH feas*.

Table A21: Robustness: Short-Time Work and DN WFH During the COVID-19 Crisis

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| *WFH DN* | -1.04*** | -0.65*** | -1.07*** | -1.03*** | -0.76*** |
| | (0.19) | (0.19) | (0.19) | (0.22) | (0.22) |
| $R^2$ | 0.26 | 0.33 | 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 WFH feasibility index proposed by Dingel and Neiman (2020). Observations correspond to NUTS-3 regions (counties) and estimates are weighted based on employment as of June 2019. For a description of control variables, see table notes of Table 1. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A22: Robustness: Short-Time Work and WFH at the Industry-Level

| | (1) | (2) | (3) | (4) |
|---|---|---|---|---|
| *WFH feas* | -0.55*** | | | |
| | (0.19) | | | |
| *WFH occ* | | -0.66*** | | |
| | | (0.21) | | |
| *WFH freq* | | | -0.99*** | |
| | | | (0.29) | |
| *WFH DN* | | | | -0.51*** |
| | | | | (0.17) |
| $R^2$ | 0.13 | 0.10 | 0.06 | 0.15 |
| NACE 2-digit industries | 88 | 88 | 88 | 88 |

*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 of 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. *WFH DN* is the feasibility index proposed by Dingel and Neiman (2020). Observations correspond to NACE 2-digit industries and estimates are weighted based on employment as of June 2019. -robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

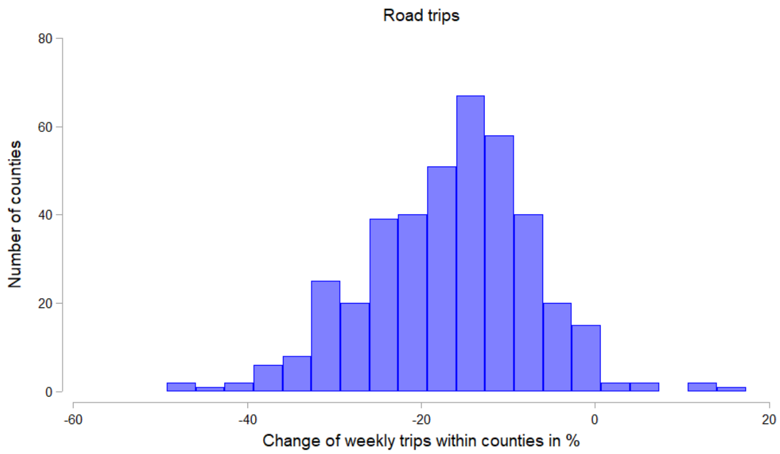
Table A23: Robustness: The Spread of SARS-CoV-2 across Counties and DN WFH

| | (1) | (2) | (3) | (4) | (5) |
|---|---|---|---|---|---|
| | | | *Log Infection Rate* | | |
| *WFH DN* | -0.033*** | -0.028** | -0.035*** | -0.038*** | -0.028** |
| | (0.0089) | (0.013) | (0.0090) | (0.0086) | (0.013) |
| $R^2$ | 0.54 | 0.60 | 0.58 | 0.62 | 0.65 |
| NUTS-3 regions | 401 | 399 | 391 | 401 | 389 |
| | | | *Log Mortality Rate* | | |
| *WFH DN* | -0.066*** | -0.063** | -0.066*** | -0.064*** | -0.058** |
| | (0.019) | (0.025) | (0.020) | (0.021) | (0.028) |
| $R^2$ | 0.27 | 0.30 | 0.29 | 0.30 | 0.33 |
| NUTS-3 regions | 369 | 367 | 362 | 369 | 360 |
| **Set of Controls** | | | | | |
| Baseline | × | × | × | × | × |
| Economy | | × | | | × |
| Health | | | × | | × |
| Social Capital | | | | × | × |

*Notes:* Dependent variable is the SARS-CoV-2 infection rate or the fatality 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 WFH feasibility index proposed by Dingel and Neiman (2020). Observations correspond to NUTS-3 regions (counties) and estimates are weighted based on population size. For a description of control variables, see table notes of Table 3. Heteroskedasticity-robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

## A.9 Details and Robustness: Changes in Mobility Patterns

Figure A6: Decline in Regional Mobility during the COVID-19 Crisis - Dingel and Neiman (2020)



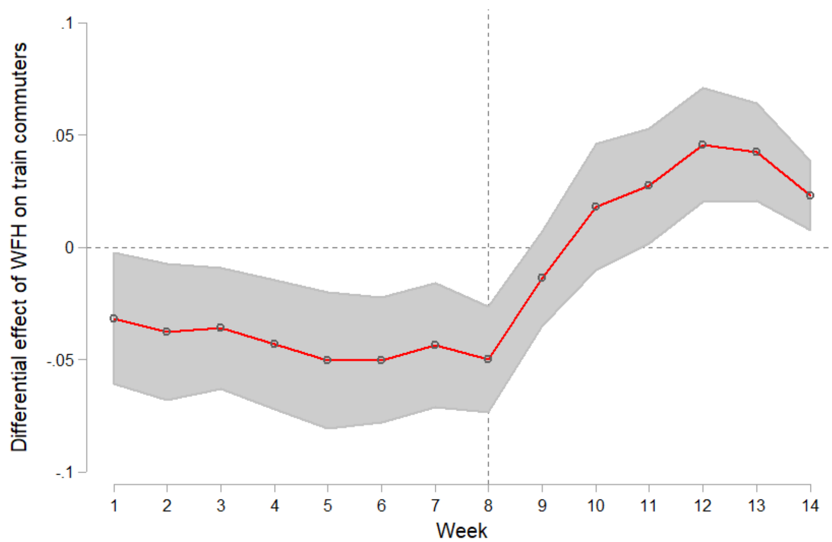

*Notes:* The Figure plots the cross-county distribution of 15-week changes in the number of car trips within counties (from week 1: Jan 23-29, 2020 to week 15: Apr 29 - May 15, 2020).

Table A24: Road Trips and Working from Home Pre- and Post-Confinement

| | (1) | (2) | (3) |
|---|---|---|---|
| WFH | -0.15*** | -0.14*** | |
| | (0.028) | (0.029) | |
| WFH × Pre confinement | | -0.033*** | -0.031*** |
| | | (0.0054) | (0.0053) |
| $R^2$ | 0.12 | 0.12 | 0.99 |
| Obs. | 6,015 | 6,015 | 6,015 |
| County F.E. | | | × |
| Week F.E. | × | × | × |

*Notes:* Dependent variable is the weekly number of road trips within a county during each week (in logs) at the NUTS-3 level based on data from Teralytics (from week 1: Jan 23-29, 2020 to week 15: Apr 29 - May 15, 2020). WFH is the percentage share of employees in the county with jobs that are frequently doing telework (*WFH freq*). *Pre confinement* is a dummy variable that indicates weeks 1-7. Observations correspond to individual weeks within NUTS-3 regions (counties). All specification control for weekly rainfall. Standard errors are corrected for clustering at the NUTS-3 county level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure A7: Robustness: The Effect of Working from Home on Train Commutes over Time




*Notes:* The Figure plots coefficient estimates of $WFH_i \times t$ (using *WFH freq*) on the log number of inbound train trips 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).