DISCUSSION PAPER SERIES

DP14871
(v. 2)

MY HOME IS MY CASTLE -- THE BENEFITS OF WORKING FROM HOME DURING A PANDEMIC CRISIS: EVIDENCE FROM GERMANY

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INTERNATIONAL TRADE AND REGIONAL ECONOMICS

LABOUR ECONOMICS

PUBLIC ECONOMICS

ISSN 0265-8003

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Discussion Paper DP14871
First Published 11 June 2020
This Revision 02 July 2020

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Abstract

This paper studies the relation between work and public health during the COVID-19 pandemic in Germany. Combining administrative data on SARS-CoV-2 infections and short-time work registrations, firm- and worker-level surveys and cell phone tracking data on mobility patterns, we find that working from home (WFH) is very effective in economic and public health terms. WFH effectively shields workers from short-time work, firms from COVID-19 distress and substantially reduces infection risks. Counties whose occupation structure allows for a larger fraction of work to be done from home experienced (i) much fewer short-time work registrations and (ii) less SARS-CoV-2 cases. Health benefits of WFH appeared mostly in the early stage of the pandemic and became smaller once tight confinement rules were implemented. Before confinement, mobility levels were lower in counties with more WFH jobs and counties experienced a convergence in traffic levels once confinement was in place.

JEL Classification: J22, H12, I18, J68, R12, R23

Keywords: COVID-19, SARS-CoV-2, Working from Home, labor supply shock, infections, mitigation, BIBB-BAuA

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Acknowledgements
We thank Andreas Steinmayr and seminar participants in Mainz and at the European Investment Bank for useful comments. We also thank Sebastian Link for sharing helpful code to compile the ifo Business Survey. Funding by the Deutsche Forschungsgemeinschaft (DFG, German Research Foundation) through CRC TR 224 (Project B06) and by the ifo Freundesgesellschaft e.V. is gratefully acknowledged.

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

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July 2020

Abstract

This paper studies the impact of working from home (WFH) on work relations and public health during the COVID-19 pandemic in Germany. Combining administrative data on SARS-CoV-2 infections and short-time work registrations, firm- and worker-level surveys and cell phone tracking data on mobility patterns, we find that working from home effectively shields workers from short-time work, firms from COVID-19 distress and substantially reduces infection risks. Counties whose occupation structure allows for a larger fraction of work to be done from home experience (i) fewer short-time work registrations and (ii) less SARS-CoV-2 cases. At the firm level, an exogenous increase in the take-up of WFH reduces the probability to file for short-time work by up to 71 p.p. and the probability of being very negatively affected by the crisis by up to 77 p.p. Much of the changes in the organization of work relations are likely to be permanent and to have effects well beyond the crisis. Health benefits of WFH appeared mostly in the early stage of the pandemic and became smaller once tight confinement rules were implemented. Before confinement, mobility levels were lower in counties with more WFH jobs and counties experienced a convergence in traffic levels once confinement was in place.

Keywords: COVID-19, SARS-CoV-2, Working from Home, Labor Supply Shock, Infections, Mitigation, BIBB-BAuA

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1 Introduction

The ongoing global COVID-19 pandemic is the most severe health crisis since the Spanish flue, costing hundred thousands of lives worldwide. In parallel with the public health calamity, the policies introduced by authorities to contain the spread of the virus have led to a harsh economic downturn. By the first week of April 2020 over half of the global population was affected by some type of confinement measure, resulting in a strong negative supply shock. In Germany, for instance, about a third of employees were registered for short-time work or lost their job in March and April 2020 (Bundesagentur für Arbeit, 2020). Developing policies to contain the pandemic while minimizing the negative impact on the economy thus remains a key challenge. In this paper we study the effectiveness of one specific policy: working from home (WFH, telework, remote work). 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.

First, we compute an index of WFH feasibility across regions and industries, 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 composition of occupations in the aggregate, in each German county and by industry. This strategy is akin to Autor et al. (2013) and Dauth et al. (2014), who exploit exogenous variation in regional economic structure to assess the labor-market impact of economic shocks. Overall, 56 percent of the workforce can work remotely (at least temporarily), while 9 percent did so on a regular basis before the pandemic. At the individual level, WFH is mainly an option for high earners and workers with frequent computer use. At the regional level, workers' skill composition and the employment share in the tertiary sector are strong predictors for the share of teleworkable jobs.

Second, we use firm-level survey data collected in April 2020 to validate our WFH measures. We show that that firms with a higher WFH capacity were significantly more likely to intensify telework as part of their mitigation strategy. A one-standard-deviation larger fraction of teleworkable jobs in the industry is associated with a 12 to 16 percentage point higher probability of firms expanding telework.

Third, we investigate whether the shift to remote work had measurable impact on economic activity. Using administrative data and firm-level survey information, we show that regions, industries and firms with a higher exogenous WFH potential experienced substantially fewer applications for the federal short-time work scheme. A one-standard-deviation increase in the share of teleworkable jobs reduces short-time work applications relative to total employment by around 4.5 percentage points at the county level and by around 9 percentage points at the industry level. At the firm level, we use our exogenous industry-level WFH measure as an instrumental variable to provide causal evidence for the employment and output-preserving effect of telework. Firms who intensified telework during the crisis are 50 to 71 percentage points less likely to file for short-time work. Furthermore, intensified telework lowers the probability of reporting adverse effects of the COVID-

19 crisis by up to 77 percentage points. Overall, our results imply that the supply-side restrictions imposed by confinement rules on firms and workers have been a key factor for reduced economic activity and that telework strongly mitigates their negative effects.

The shift to telework will likely have lasting effects on the economy. While short-time work schemes have proved effective in keeping unemployment low in previous recessions (Balleer et al., 2016) this came at the expense of significant allocational inefficiencies (Cooper et al., 2017). By contrast, WFH generates no such allocational inefficiencies since teleworkers continue to perform their jobs at full cost to the firm. Moreover, since previous recessions have often been characterized by jobless recoveries (see Jaimovich and Siu, 2020) and because the current downturn will last much longer than initially expected, short-time work is unlikely to prevent unemployment in the long-run. In addition, the shift to remote work is likely to persistently affect the organization of work. Many hurdles and reservations against WFH have been dismantled within a short period of time: work processes have been digitized, employees have been equipped with communication tools and the stigma of the lazy homeworker has disappeared. Once these sunk investments have been made, it is optimal for companies to adjust their organizational structure permanently.[1] In line with this intuition, 54 percent of German firms plan to maintain a higher level of telework beyond the pandemic (ifo Business Survey, May 2020). Previous research suggests that WFH can have sizable productivity benefits at the worker level (Bloom et al., 2014). As such effects are unlikely to fully materialize in the short-term due to adjustment costs (e.g., no telework experience, lack of equipment) and the precarious situation during the crisis (e.g., child care duties), our results are likely to underestimate the positive long-term impact of telework on firm outcomes.

Finally, we investigate the impact of working from home on SARS-CoV-2 infections both before and after strict confinement rules were imposed in Germany. While the first cases of SARS-CoV-2 in Germany were recorded in late January, the pandemic began to really pick up in early March with people returning from skiing holidays in Austria (Felbermayr et al., 2020). In the meantime, authorities gradually ratcheted up restrictions on public life (see Weber, 2020 for details). On March 22, all German states imposed severe confinement measures in a coordinated manner.[2] We exploit detailed weekly panel data on SARS-CoV-2 infections and deaths from January 29 to April 15, 2020 for all 401 counties. Using cross-sectional variation, we find that a one-standard-deviation exogenous increase in the WFH share is associated with a 10 to 15 percent reduction in the infection rate and a 22 to 37 percent reduction in the fatality rate. Moreover, the infection-reducing effect of working from home is larger in the first weeks of the pandemic. Exploiting within-county variation, we find an on average around 8 percent larger reduction in the infection rate before the confinement. The effectiveness of WFH is also independent of differences in the confinement strictness across states. These results are consistent with mobility data collected from a large German mobile phone provider. Mobility patterns show that the level of work-related trips was systematically lower in high-WFH-

[1] This argument is similar to the *trapped-factor* argument of innovation triggered by competition (see Bloom et al., 2013).

[2] Exceptions were Bavaria and Saxony, which started confinement already a day earlier.

ability regions before confinement but that this differential disappeared once the lockdown was in place and everyone stayed at home. Finally, we also show that our results are robust to using a state-of-the-art dynamic spatial count model borrowed from the epidemiology literature (Höhle, 2015, Meyer et al., 2017). Overall, our findings imply that working from home and confinement are 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 working from home should be a policy prescription as long as infection risks remain present.

Our study relates to the literature studying telework and the effects of social distancing during the COVID-19 pandemic. A comprehensive review of the rapidly expanding literature on the economic effects of the COVID-19 crisis is beyond the scope of this paper. We thus mention just a few of the most closely related studies. First, we add to 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. Variants of this approach have been proposed in other studies and extended to other countries.[3] We draw instead on an administrative employee survey that directly reports on workers' home-working practices before the COVID-19 outbreak (see Alipour et al., 2020). This survey approach ensures that assessments about the teleworkability of jobs are based on workers' own assessments and experiences. Möhring et al. (2020) and Von Gaudecker et al. (2020) instead measure the endogenous take-up of WFH during the COVID-19 pandemic based on employee-survey data.

Second, we contribute to the literature studying the costs and benefits of social distancing. Barrero et al. (2020) and Buchheim et al. (2020) use firm-level survey data to study how the COVID-19 shock induced firms to adjust to the crisis. Papanikolaou and Schmidt (2020) show that industries with high WFH shares experienced lower declines in employment and earnings forecasts. Based on a survey of workers, Adams-Prassl et al. (2020) document a negative correlation between workers' self-reported share of teleworkable task and the probability of job loss during the COVID-19 pandemic. In accordance with these results, we verify that our WFH proxies predict firm-level responses in staffing (taking up WFH and short-time work registrations). Furthermore, we provide causal evidence that an increase in WFH mitigates the negative impact of the crisis at the firm level, both in terms of less short-time work registrations and economic distress. Barrot et al. (2020) and Fadinger and Schymik (2020) study the output losses induced by negative labor supply shocks in input-output models for France and Germany, respectively estimating a weekly loss of about 1% (1.6 %) of French (German) GDP. We add to their results by providing empirical evidence that WFH indeed mitigates negative labor supply shocks very effectively. Hartl et al. (2020) identify a trend break in German SARS-CoV-2 infections growth subsequent to the implementation of social distancing policies. In line with our infection-reducing effects of working from home, Chiou and Tucker (2020) report that IT infrastructure in homes increases individuals' ability to self-isolate. Koren and Peto (2020) show that U.S. businesses that require face-to-face communication or close

[3]See for instance Mongey et al. (2020), Yasenov (2020), Barbieri et al. (2020), Boeri et al. (2020) or Holgersen et al. (2020).

physical proximity are particularly vulnerable to confinement. This is consistent with our finding that those firms are also more likely to experience distress and register their workers for the German short-time work scheme.

In the next Section, we describe the construction of regional and sectoral measures of WFH from individual-level survey data and show that these measures strongly correlate with WFH take-up during the COVID-19 crisis. In Section 3, we examine in detail the effect of exogenous variation in WFH on region-, firm- and industry-level short-time work and firm distress. In Section 4, we look at the relationship between WFH and SARS-CoV-2 infections and fatalities at the county level, both before and after confinement, and we study regional variation in mobility patterns during the COVID-19 crisis. Finally, Section 6 presents our conclusions.

2 Measuring Working from Home in Germany

We are interested in the proportion and the geographical distribution of jobs that can be performed at home in Germany. In the recent literature different approaches to measure working from home (WFH) feasibility have emerged. One set of studies draw on country-specific surveys that directly report on workers' home-working practices before the COVID-19 outbreak (Alipour et al., 2020, Hensvik et al., 2020, Watson, 2020, Irlacher and Koch, 2020). Alternatively, Dingel and Neiman (2020) determine the teleworkability of occupations by assessing the importance of workers' presence at the workplace using task information from O*NET (Occupational Information Network).[4] The main advantage of the survey approach compared to using task information is that assessments about the teleworkability of jobs are independent of researchers' plausibility judgments but instead based on workers' own assessments.

We thus follow Alipour et al. (2020) and combine worker-level information from the 2018 wave of the BIBB/BAuA Employment Survey with employment counts from the Federal Employment Agency (BA) to measure homeworking patterns across 401 counties (*Kreise* and *kreisfreie Städte*).[5] The employment survey contains rich information about worker characteristics and the nature of their jobs. We restrict the sample of respondents to 17,160 employed individuals aged 18-65 (excluding marginal and self-employment) who report about their working from home habits. Based on this information, we compute three measures: First, 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 have ever worked from home or who do not exclude the possibility of home-based work, provided

[4]Variants of this measure have been proposed by other studies and for other countries (Mongey et al., 2020, Yasenov, 2020 Barbieri et al., 2020 , Boeri et al., 2020, Holgersen et al., 2020, Fadinger and Schymik, 2020).

[5]The 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 information about 20,012 individuals surveyed between October 2017 and April 2018; for more details see Hall et al. (2020).

the company grants the option (*WFH feas*).[6] The latter measure hence identifies jobs which can (at least partly) be done from home, independently of a worker's previous homeworking experience. Consequently, we interpret the proportion of *WFH feas* in the overall workforce as an upper bound for the share of employees who may work from home during the crisis. As switching to remote work during the pandemic is arguably associated with transition costs, we conjecture that frequent and occasional homeworkers will be able to use telework earlier and to a greater extent than employees who have no previous homeworking experience. We therefore interpret *WFH freq* as a lower-bound estimate for the share of employees actually working remotely during the pandemic.

2.1 Who Can Work from Home? Individual-Specific Variation

Table 1 reports conditional correlations from regressing binary indicators for *WFH freq* and *WFH feas* at the worker level on individual characteristics and a set of occupation and sector fixed effects.[7] Occupational variation alone explains 21% and 27% of the variation in *WFH freq* and *WFH feas*, respectively (columns 1 and 4). Including 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. In terms of workplace characteristics, having management responsibilities and using computers at work are strongly associated with the possibility to work from home. The result is in line with previous findings that WFH is mainly possibly in jobs requiring cognitive, non-manual tasks (Mergener, 2020). Holding an academic degree also increases the chance of both having a WFH feasible job and actually engaging in remote work. By contrast, marital status and having children in the household do not significantly impact the likelihood of having a teleworkable job; however, these factors affect the selection into actually taking up remote work. Finally, we find no significant gender differences within occupations.

Observe that WFH is mainly an option for high earners. In the top quintile of the wage distribution more than 80% of workers could work from home at least temporarily, and about 60% actually did so before the pandemic. By contrast, only 45% of workers in the bottom quintile have a teleworkable job, with less than 20% having any remote work experience. This disparity coincides with the differences across professional qualifications (see Figure 8 in the Appendix). In terms of industry variation in WFH, the share of teleworkable jobs is highest in the service sector, which also has the highest share of frequent PC users (76% versus 65% in the rest of the economy).

2.2 Regional Variation in Working from Home

In order to derive the geographical distribution of teleworkable jobs, we aggregate our measures to the occupational level (based on 36 KldB-2010 2-digit occupations, excluding military services)

[6] Specifically, individuals were asked: "If your company allowed you to work at home temporarily, would you accept this offer?" – *Yes; No; Is not possible with my work.*

[7] 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 1: Conditional Correlations between WFH and Worker Characteristics

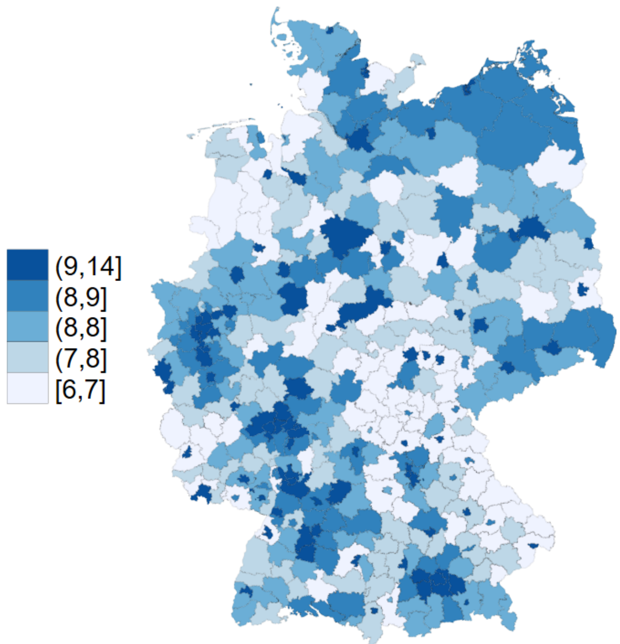
	WFH frequently			WFH feasible		
	(1)	(2)	(3)	(4)	(5)	(6)
Female		-0.01	-0.01		0.01	0.01
		(0.01)	(0.01)		(0.01)	(0.01)
Migrant		-0.03***	-0.03***		-0.02	-0.02
		(0.01)	(0.01)		(0.02)	(0.02)
Married		0.02***	0.02***		0.01	0.01
		(0.01)	(0.01)		(0.01)	(0.01)
Children		0.02***	0.02***		0.01	0.01
		(0.01)	(0.01)		(0.01)	(0.01)
Academic degree		0.08***	0.08***		0.18***	0.17***
		(0.01)	(0.01)		(0.01)	(0.01)
Part-time		0.00	0.00		-0.01	-0.01
		(0.01)	(0.01)		(0.01)	(0.01)
Manager		0.04***	0.04***		0.07***	0.08***
		(0.01)	(0.01)		(0.01)	(0.01)
PC usage		0.05***	0.05***		0.15***	0.15***
		(0.01)	(0.01)		(0.02)	(0.02)
Occupation F.E	yes	yes	yes	yes	yes	yes
Sector F.E	no	no	yes	no	no	yes
R^2	0.21	0.23	0.24	0.27	0.31	0.31
Observations	17,130	16,065	15,938	17,112	16,046	15,920

Notes: The dependent variable in columns (1) - (3) is a binary variable identifying workers 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. Part-time is an indicator identifying workers with contractual working time of less than 30 hours per week. Other control variables include age, age-squared and an ordinal variable for 3 plant size categories (outputs suppressed). 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

and combine the resulting shares with information from the Federal Employment Agency (BA) on the composition of occupations in each county.[8] County-specific WFH shares are subsequently computed as a weighted average over occupations. Hence, by construction, regional differences in WFH feasibility are determined exclusively by county-level differences in occupational composition. Remember that the bulk of the individual-specific variation in telework that can be explained by observables is due the occupational variation. Our region-specific WFH measures thus exploit most

[8]Employment counts by county and occupation are taken from the German Federal Employment Agency's June 2019 regional employment report (*Regionalreport über Beschäftigte*). See Table 17 in the Appendix for occupation-specific WFH shares.

Figure 1: Geographical Distribution of Pre-Crisis Frequent Homeworkers



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

of the individual-specific variation in telework. In the aggregate, about 9% of employees work from home on a regular basis, 26% do so at least occasionally, and 56% have jobs which in principle can be partly or completely performed at home. Table 2 reports detailed summary statistics of our regional WFH measures.

The geographical distribution of pre-crisis frequent homeworkers (*WFH freq*) across 401 NUTS-3 regions is depicted in Figure 1. The share of teleworkable jobs measured by any metric is higher in more urban, more affluent counties. Local GDP per capita and *WFH freq* are strongly correlated at about 0.50. The association of WFH with higher education and employment in the service sector is particularly striking at the regional level. The correlation with *WFH freq* is about 0.9 and 0.7, respectively (see Figure 9 in the Appendix), indicating a high degree of co-linearity. Together these two variables explain almost 90% of the regional variation of *WFH freq*.

2.3 Working from Home Measures and Adoption of Firm-Level Remote Work During the COVID-19 Crisis

The COVID-19 crisis has forced many companies to embrace remote work within a short period of time. Recent surveys document that the proportion of the workforce working from home has indeed dramatically increased in Germany. For instance, in an online survey of more than 85,000

Table 2: Summary Statistics of WFH Measures at the County-Level

		Mean	Std. Dev.	Min	25th	Median	75th	Max
WFH feasible	(*WFH feas*)	52.69	4.18	45.55	49.73	51.50	54.82	67.47
WFH occasionally	(*WFH occ*)	23.52	3.04	18.40	21.47	22.54	24.82	36.14
WFH frequently	(*WFH freq*)	8.47	1.33	5.98	7.56	8.02	8.99	14.30

Notes: The table reports descriptive statistics for our three WFH measures across 401 NUTS-3 regions in Germany.

individuals across several EU states, 37% of German respondents reported to have started telework as a result of the COVID-19 crisis (Eurofound, 2020).[9]

To investigate if our WFH measures are associated with actual changes in telework patterns during the COVID-19 crisis, we test if firms in industries with a larger fraction of teleworkable jobs according to our measures are more likely to expand WFH during the COVID-19 crisis. To this end, we draw on the April 2020 wave of the ifo Business Survey (IBS). The IBS is a monthly representative survey of German firms which collects data on various company parameters as well as current business conditions and business expectations (see Buchheim et al. (2020) and Sauer and Wohlrabe (2020) for a more detailed description of the survey).[10] In April 2020 roughly 6,000 firms were questioned about the business impact of and the managerial responses to the COVID-19 pandemic. Among a list of non-exclusive mitigation measures, the most frequently mentioned response was the intensified use of telework.[11] Overall, almost two third of the companies stated increased reliance on telework as part of their strategy to cope with the crisis. Using this information allows us to compare firms' responses with our WFH measures computed at the industry level. To calculate sectoral WFH shares, we use information from the Federal Employment Agency (BA) on the sectoral composition of occupations and apply the same approach as for the calculation of county-level WFH shares (see Section 2).

Table 3 reports the coefficients from regressing a firm-level indicator identifying firms who reported intensified telework on our industry-level WFH measures. To make our WFH measures quantitatively comparable with each other, we normalize them to mean zero and a unit standard deviation (z-scores). All specifications include controls for firm-size (5 size categories), the share of sales generated abroad, fixed effects for the date of survey completion, location fixed effects at the county level and survey fixed effects, which correspond to the broad industry segments Services, Wholesale/Retail, Construction and Manufacturing (coefficients not reported). In the even columns we

[9]Schröder et al. (2020) find that across all employed persons, around 34% worked partly or completely from home in April 2020. This share reaches even 60% among employees with an university degree. Kohlrausch and Zucco (2020) surveyed 7,677 persons in April 2020 and find that the share of employees working mainly onsite dropped from 87% to 55% for women and from 79% to 51% for men.

[10]We use a harmonized version of the data following the harmonization procedure proposed by Link (2020).

[11]Other answers included, e.g., "introducing short-time work", "reduction of time accounts and leave days", "Cut of employment", "application for public liquidity facilities", "postponement of investments" and "cancellation of investments".

additionally control for firms' average state of business as well as expected business conditions for the next six months during the forth quarter of 2019. We hence take into account firms' pre-crisis conditions, which are likely to affect the choice of mitigation strategies during the pandemic. Business states and outlooks are elicited on a ordinary scale (negative, neutral, positive). Moreover, we add a dummy for firms operating in a sector that was subject to a mandatory shutdown. To account for demand-side effects of the crisis, we also include a dummy equal to one if a firm reports that the crisis has adversely affected demand. As the question is not put to firms in the construction sector we report the results separately in Table 18 in the Appendix. In all specifications standard errors are clustered at the 2-digit NACE 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 highly significant increase in the probability to expand remote work during the crisis. In terms of magnitudes, increasing *WFH freq* by one standard deviation increases the probability that a firm intensifies remote work during the COVID-19 crisis by 12.22 percentage points. The effects for *WFH occ* (14.88 p.p.) and *WFH feas* (15.72 p.p) are even larger. The coefficient magnitudes are just slightly reduced and remain highly significant when controlling additionally for pre-crisis conditions and the shutdown dummy in columns (2), (4) and (6). The effect of mandatory business closures is strongly negative, which is explained by the fact that firms operating in sectors such as accommodation, restaurants and retail trade do not rely much on telework. Finally, firms reporting an unfavorable state of business before the crisis are less likely to take-up of remote work relative to firms in a neutral state.

In principle, firms can expand telework both at the intensive and the extensive margin, i.e., by increasing the number of hours that each employee works at home or by introducing employees without previous teleworking experience to remote work. As *WFH feas* captures WFH feasibility independently of previous experience, the estimates in column (5) and (6) can be interpreted as the combined effect at both margins. Columns (7) and (8) distinguish between the share of workers with pre-crisis WFH experience (*WFH occ*) and those without WFH experience but with a teleworkable job (*WFH unexploited*).[12] Both coefficients are positive and significant at the one-percent level, indicating that firms indeed expanded remote work at both margins. The estimate associated with *WFH occ* in column (7) suggests that a one-standard-deviation increase in the share of workers with pre-crisis telework experience is associated with a 11.88 p.p. increase in the probability to intensify remote work. By contrast, a one-standard-deviation increase in the share of unexploited WFH potential translates in a much smaller probability increase to intensity remote work of 5.69 p.p. The weaker extensive-margin response plausibly reflects adjustment costs from newly setting up remote workplaces and the fact that, by our definition, not every teleworkable job is necessarily suitable for full-time remote working. Overall, the evidence strongly supports that our WFH measures capture actual telework expansion at the firm level during the COVID-19 crisis.

[12]Specifically, unexploited WFH is defined as the difference between the sector-level shares of *WFH feas* and *WFH occ*.

Table 3: Intensified Telework Due to COVID-19 and WFH Potential – Firm-Level Evidence

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
WFH freq (z-score)	12.22***	9.58***						
	(1.99)	(1.00)						
WFH occ (z-score)			14.88***	11.46***			11.88***	9.61***
			(2.70)	(2.08)			(1.92)	(1.78)
WFH feas (z-score)					15.72***	12.33***		
					(2.16)	(1.52)		
WFH unexploited (z-score)							5.69***	4.13***
							(1.74)	(1.30)
Mandatory shutdown		-25.78***		-20.85**		-18.46**		-18.54**
		(9.62)		(8.01)		(7.12)		(7.18)
Business outlook 2019Q4								
negative		-1.96		-1.65		-1.29		-1.32
		(1.53)		(1.52)		(1.50)		(1.51)
positive		4.48***		4.50***		4.59***		4.57***
		(1.60)		(1.61)		(1.62)		(1.62)
State of business 2019Q4								
negative		-4.01***		-3.89***		-3.71***		-3.73***
		(1.38)		(1.38)		(1.39)		(1.40)
positive		1.05		0.48		0.32		0.33
		(1.81)		(1.68)		(1.56)		(1.57)
County F.E.	yes	yes	yes	yes	yes	yes	yes	yes
R^2	0.29	0.33	0.31	0.34	0.32	0.34	0.32	0.34
Firms	6,580	5,649	6,580	5,649	6,580	5,649	6,580	5,649

Notes: The dependent variable is an indicator (rescaled by 100) identifying firms who report an intensified usage of telework in response to the COVID-19 crisis in April 2020. WFH is the z-score (mean 0, standard deviation 1) of the percentage share of employees in the NACE-2 industry with jobs that are feasible for telework (*WFH feas*) or who either occasionally (*WFH occ*) or frequently (*WFH freq*) work from home as defined in Subsection 2. The variable *WFH unexploited* represents the share of workers with a teleworkable job but without any previous remote working experience. Controls include a dummy variable identifying firms operating in a sector subject to mandatory business closures, controls for pre-crisis business conditions and expected future state of business in Q4 2019 (relative to a neutral state) and location fixed effects at the county level. Additional controls (not reported) include firm size fixed effects (5 size categories), the share of sales generated abroad, fixed effects for the date of survey completion and survey fixed effects (Construction, Wholesale/Retail, Service and Manufacturing). Data are from the ifo Business Survey. Standard errors clustered at the NACE-2 level reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

3 Working from Home and Labor Market Adjustments in Germany during the COVID-19 Crisis

To contain the spread of the coronavirus, the German government enforced drastic social distancing measures. Many companies, especially in the hospitality, food services and retail sector were subjected to mandatory shutdowns to mitigate infection risks. At the same time, a large fraction of firms switched to remote work to minimize exposure of their workers to the virus (see Section 2.3). The consequences of the economic shock are reflected in the employment statistics. In Germany, filings for short-time work (STW) allowances reached a historic level. The short-time work scheme (*Kurzarbeit*) 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. Previous research indicates that short-time work schemes can be very effective in retaining employment and avoiding mass layoff during economic crises (see e.g. Balleer et al., 2016; Boeri and Bruecker, 2011). In March and April 2020, STW applications for 10.7 million workers were filed, corresponding to 31% of total employment in September 2019.[13] In comparison, this number reached only 3.3 million during the Great Recession in 2008/2009 (Bundesagentur für Arbeit, 2020). Finally, in Germany most of the short-run labor market adjustments to the COVID-19 shock occurred in terms of short-time work expansions and only very little happened via an increase in unemployment.[14]

The key question we address in this Section is whether the possibility to work remotely mitigates the COVID-19 shock by increasing the likelihood that workers can continue to do their job instead of being put on short-time work. We examine this relationship by estimating the impact of WFH on short-time work applications first at the regional and then at the industry and the firm level. To this end, we source comprehensive administrative records on STW applications in March and April 2020, at the NUTS-3 level from the Federal Employment Agency (*Bundesagentur für Arbeit*).

3.1 Working from Home and Short-time Work: Regional and Industry Evidence

We start by analyzing the relationship between STW applications and WFH at the regional level. Figure 2 plots the raw correlation between the share of employees affected by STW and the fraction of frequent teleworkers (*WFH freq*) across 401 counties. As is apparent from the Figure, the relationship is strongly negative, indicating that regions with a higher level of *WFH freq* have fewer STW applications relative to their workforce.

When interpreting the negative relationship between working from home and short-time work as causal, one may be concerned about endogeneity for two reasons. First, regions hit more harshly by the pandemic likely have a larger fraction of short-time work applicants, as more firms are forced to shut down, and at the same time also have a larger share of workers working remotely for safety reasons. Note that our WFH measures are completely insulated from such reverse causality because they are based on interactions between pre-Corona occupation-level variation in telework and regional occupational employment composition. Second, there may be omitted regional characteristics that are negatively correlated with the STW application shares and positively with the fraction of teleworkable jobs. For example, rural areas may have a lower infection risk due to low population density and thus less short-time work and at the same time also a higher share of teleworkers due to high commuting costs. We thus control for a wide range of region-specific covariates that are plausibly related to STW applications and working from home. These include county-level

[13] The proportion is essentially identical when measured relative to employment in June 2019, which represents our reference period.

[14] In contrast to the unemployment surge in the U.S. (see Coibion et al., 2020), the net number of unemployed in Germany increased by less than 250,000 in March and April 2020.

income, productivity and density measures (log GDP, log labor productivity, log population, log settled area), age structure (the share of working age population, the share of residents older than 74), infrastructure (the fraction of (in- and outward) commuters in the local workforce and the reachability of the nearest international airport). We further control for regional sector composition by including the employment shares in the Accommodation and Food Services (NACE section I), Manufacturing (C), Wholesale/Retail (G) and the financial sector (K), respectively. See Table 16 in the Appendix for details on variable sources and reference dates.

Table 4 reports the corresponding OLS coefficient in column (1) together with the analogous estimates for our remaining WFH measures in the other odd columns. Again, to make the coefficients for the three measures comparable, we transform them to z-scores. The even columns add county-level controls. We weight county-level regressions with population weights 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. The relationship between WFH capacity and STW applications is negative and significant at the one-percent level across all specifications. A one-standard-deviation increase in *WFH freq* results in a reduction of the number of STW applications relative to the total regional work force of 2.52 percentage points, which is substantial. The magnitude of the coefficient slightly drops to 2.03 p.p. when controlling for county characteristics (column 2).[15] Similarly, a one-standard-deviation increase in *WFH occ* decreases the STW share by 2.17 p.p (2.16 p.p. when including controls) (columns 3 and 4). Finally, a one-standard-deviation increase in *WFH feas* is associated with a 1.91 p.p. (1.84 p.p) drop in the STW share (columns 5 and 6). The results hence strongly support the hypothesis that regions with a larger share of employees who can work remotely are less affected by short-time work.

To provide further evidence that regional variation in STW applications is indeed driven by exogenous variation in the regional occupation composition, we now analyze the relationship between administrative STW applications and our WFH measures at the industry level. To this end, we aggregate STW applications at the NACE-2 industry level and correlate them with our industry-level WFH measures. If industries with higher WFH shares suffered a smaller reduction in labor supply because their workers could continue to work safely from home, they would be hit less severely by the COVID shock. Table 5 reports the results of regressing industry-level STW shares on our WFH measures (normalized to z-scores). The negative association between WFH shares and STW applications is even stronger at the industry level than at the region level: a one-standard-deviation increase in *WFH freq* is associated with a 4.46 p.p. drop in the industry-level STW application share. The magnitudes of this effect are even larger when using the other WFH measures (-6.68 p.p and -8.13 p.p.).

[15] The estimates are robust to measuring STW shares relative to employment in September or March 2019 instead of June 2019.

Table 4: Short-Time Work and WFH During the COVID-19 Crisis – County-Level Evidence

	(1)	(2)	(3)	(4)	(5)	(6)
WFH freq (z-score)	-2.52***	-2.03***				
	(0.41)	(0.76)				
WFH occ (z-score)			-2.17***	-2.16***		
			(0.44)	(0.77)		
WFH feas (z-score)					-1.91***	-1.84**
					(0.48)	(0.88)
Controls	no	yes	no	yes	no	yes
R^2	0.16	0.38	0.13	0.37	0.10	0.37
Population weights	yes	yes	yes	yes	yes	yes
NUTS-3 regions	401	390	401	390	401	390

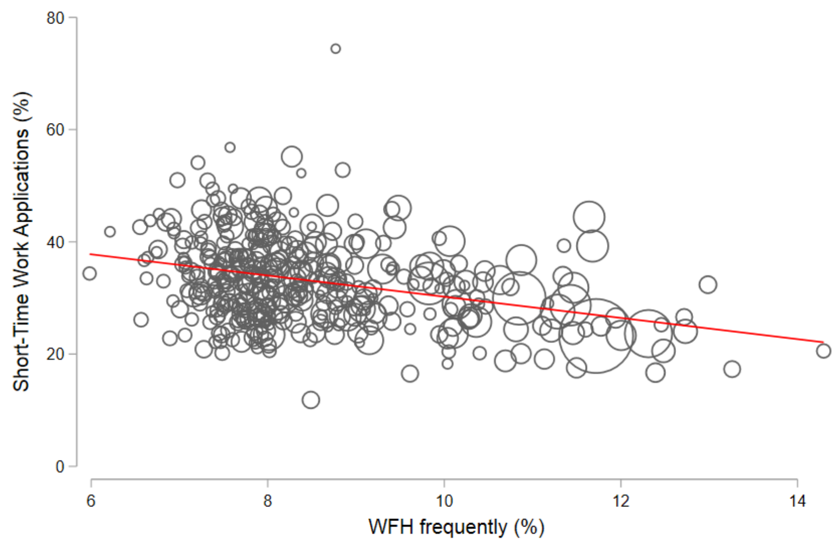
Notes: Dependent variable is the percentage of the total number of persons mentioned in short-time work applications in March and April 2020 relative to employment in June 2019. Control variables include log GDP, log labor productivity, log population, log settled area, the share of working age population, the share of residents older than 74, the fraction of (in- and outward) commuters in the local workforce, the reachability of the nearest international airport and the share of employment in the Accommodation and Food Services, Manufacturing, Wholesale/Retail and the financial sector, respectively. Regions are weighted with total population. Employment and short-time work data are from the Federal Employment Agency (BA). Robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 5: Short-Time work and WFH During COVID-19 Crisis – Industry-Level Evidence

	(1)	(2)	(3)
WFH freq (z-score)	-4.45***		
	(1.32)		
WFH occ (z-score)		-6.68***	
		(2.14)	
WFH feas (z-score)			-8.13***
			(2.81)
R^2	0.06	0.10	0.13
NACE-2 Industries	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. Industries are weighted with total employment in June 2019. Industry-level information on employment and short-time work are obtained from the Federal Employment Agency (BA). Robust standard errors reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure 2: WFH and Short-Time Work During the COVID-19 Crisis



Notes: The figure depicts the linear fit between the share of workers affected by short-time work and the pre-crisis share of frequent homeworkers (*WFH freq*) across 401 NUTS-3 regions. STW shares are defined as the ratio of the total number of persons mentioned in short-time work applications in March and April 2020 relative to employment in June 2019. Counties are weighted with total population. Employment and short-time work data are from the Federal Employment Agency (BA).

3.2 Working from Home and Short-Time Work: Firm-Level Evidence

Next, we analyze the relationship between STW applications and our WFH measures at the firm level drawing on data from the April 2020 wave of the ifo Business Survey, discussed in Section 2.3 above. The IBS not only includes the indicator for intensified use of telework, but also a question if firms have responded to the COVID-19 crisis by filing for short-time work. Overall, about half of the firms report using the short-time work scheme.

Compared to using the regional- or industry-level variation, the firm-level analysis has several advantages. First, we have firm-level measures of both, short-time work and telework available. However, firms that are affected more severely by the COVID-19 crisis likely respond by filing for short-time work, while also relying on the increased use of telework. This would lead us to underestimate the employment preserving effect of working from home in an OLS regression. Fortunately, we can use our exogenous measures of industry-level WFH as an instrument for take up of telework that is orthogonal to firms' idiosyncratic COVID-19 shocks and, as shown above, strongly correlated with increased use of telework. Since firms expanded WFH both at the intensive and the extensive margin (see Table 3), we use *WFH feas*, which measures the overall share of teleworking jobs in a given industry, as our preferred instrument. Second, the firm-level analysis allows us to cleanly separate supply from demand shocks. On the one hand, telework may mitigate the reduction in labor supply due to confinement and thus lead to reduced STW applications. On the other hand, firms may experience negative demand shocks that lead to a fall in output and an increase in STW. This would lead to a spurious positive correlation between WFH and STW if negative demand shocks are larger in sectors with a low WFH share. This is a concern in particular for the restaurant, retail and hospitality sectors. In some specifications we thus directly control for the self-reported impact of the COVID-19 crisis on firms' demand.

Table 6 presents reduced-form, OLS and IV regressions of the firm-level indicator for STW application on the firm-level indicator of intensified telework, using *WFH feas* as an instrument. These regressions include the same fixed effects and controls as those in Table 3 (see Section 2.3 above and the table notes for details). To additionally control for demand-side effects of the crisis we further add an indicator for firms who report that the crisis has negatively affected demand. Since this information is not available for firms in the construction sector, we separately report the results in columns (1) - (3) of Table 19 in the Appendix. In columns (1) and (2), we report the reduced-form result of directly regressing the outcome variable on the instrument. *WFH feas* is negatively correlated with the firm-level probability to file for STW and significant at the one-percent level. This is robust to controlling for the state of business, the business outlook and a dummy for the industry being subject to mandatory shutdown. Columns (3) and (4) report the OLS results: the firm-level indicator for intensified telework is negatively correlated with the probability to file for STW and significant at the one- (column 3) or ten-percent level (column 4). Using increased telework reduces the probability of filing for STW by 11 (4) percentage points. However, as explained above, the OLS estimate is likely to be downward biased in absolute magnitude due to unobserved idiosyncratic Corona shocks. Indeed, the IV estimates presented in columns (5) and (6) are substantially larger and significant at the one-percent level: relying on increased telework reduces the firm-level probability to rely on short-time work by 71 (50) percentage points. Finally, controlling for the demand-side shock of the crisis does not affect the results (Table 19). Firms experiencing a drop in demand due to the crisis are significantly more likely to apply for short-time work. The same is true for firms that report a bad state of business before the crisis. Overall, our results show that working from home is extremely effective in reducing short-time work filings.

We argued that the IV estimates of telework on STW applications correct for the fact that firms applying for STW tend to be hit particularly hard by the COVID-19 shock. We provide direct evidence for this by exploiting information on the self-assessed severity of the COVID-19 crisis from the IBS. Indeed, about 30% of the firms state a "very negative" impact of the crisis to business in April 2020. Table 7 reports OLS and IV results from regressing an indicator identifying these firms on a dummy for companies who intensified telework during the crisis and on our instrument *WFH feas*. We again control for firm size, firm location, firms' export share and survey fixed effects (coefficients not reported). The even columns additionally include a dummy for mandatory shutdown and pre-crisis business state and business outlook. Again, we separately report the results for specifications which control for the demand-side shock of the crisis, as we do not have the information for firms in the construction sector (see columns 4 - 6 of Table 19 in the Appendix).

The OLS estimates indicate that increased telework is negatively correlated with being negatively affected by the COVID-19 shock (a 7 to 15 percentage point reduction). However, this effect is much smaller than the causal IV estimate, according to which the intensified use of telework reduces the probability of the firm being very negatively affected by the COVID-19 crisis by 50 to 71 percentage points (columns 5 and 6). The results further indicate that firms who appear weaker before the crisis are also more strongly affected by the COVID-19 shock. A negative (positive) state of business in Q4 of 2019 increases (reduces) the likelihood of a very negative COVID-19 impact by 9.8 (9.3) percentage points relative to a neutral business state before the crisis (column 6). These findings are in line with Buchheim et al. (2020) who show that the crisis has reinforced preexisting business weaknesses. Finally, controlling for the demand side-effect of the crisis does not substantially change the results. Firms experiencing a demand drop are more likely report a very negative impact of the crisis (Table 19). Overall, the results suggest that the expansion of telework during the crisis had a sizable mitigating effect on the severity of the COVID-19 shock for firms.

4 Working from Home and the Spread of COVID-19 across German Counties

We now turn to the impact of working from home on SARS-CoV-2 infections. We expect working from home to reduce coronavirus infections for the following reasons. A higher WFH share at the county level is associated with a smaller fraction of workers working on site. This directly reduces the contact rate – defined as the average number of contacts of an infected individual, which is a key parameter in infectious disease models (Giesecke, 2002) – by reducing the number of personal contacts both at work and while commuting. In addition, a larger share of workers engaging in telework also allows co-workers who have to work on site keeping more physical distance, thereby also reducing transmission of the disease between these workers. In this section we study the effectiveness of WFH in reducing SARS-CoV-2 infections empirically.

4.1 Measuring SARS-CoV-2 Infections and Fatalities

To measure SARS-CoV-2 infections and fatality cases in Germany, we use administrative data provided by the Robert-Koch-Institut (RKI). 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.[16] 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

[16] See Infektionsschutzgesetz (IfSG).

Table 6: Effect of Working from Home on Short-Time Work – Firm-Level Evidence

	RF		OLS		IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Intensified telework			-11.03***	-4.06*	-71.11***	-49.80***
			(3.86)	(2.18)	(11.22)	(14.72)
WFH feas (z-score)	-11.18***	-6.14***				
	(2.66)	(1.68)				
Mandatory shutdown		28.12***		33.44***		18.92**
		(5.90)		(6.26)		(7.16)
Business outlook 2019Q4						
negative		2.11		2.58		1.46
		(2.00)		(2.10)		(2.33)
positive		2.03		2.10		4.31*
		(2.11)		(2.11)		(2.22)
State of business 2019Q4						
negative		12.31***		12.47***		10.46***
		(1.82)		(1.89)		(2.10)
positive		-10.00***		-10.45***		-9.84***
		(1.56)		(1.65)		(1.62)
County F.E.	yes	yes	yes	yes	yes	yes
R^2	0.14	0.20	0.12	0.19		
Wald F					52.92	65.65
N	6,580	5,649	6,580	5,649	6,580	5,649

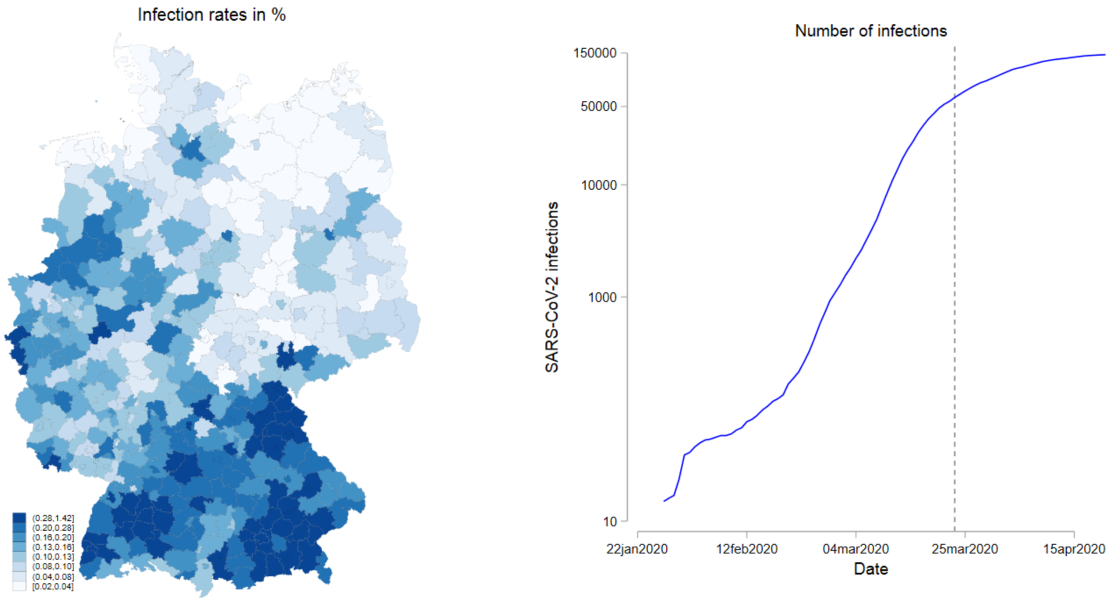
Notes: The dependent variable is an indicator (rescaled by 100) identifying firms who participated in the Short-Time Work scheme due to the COVID-19 crisis in April 2020. *WFH feas* is the z-score (mean 0, standard deviation 1) of the percentage share of employees in the NACE-2 industry with jobs that are feasible for telework (*WFH feas*) as defined in Subsection 2. *Intensified telework* is a binary variable identifying firms who report an intensified usage of telework in response to the COVID-19 crisis in April 2020. Controls include a dummy variable identifying firms operating in a sector subject to mandatory business closures, controls for pre-crisis business conditions and expected future state of business in Q4 2019 (baseline: neutral) and location fixed effects at the county level. Additional controls (not reported) include firm size fixed effects (5 size categories), the share of sales generated abroad, fixed effects for the date of survey completion and survey fixed effects (Construction, Wholesale/Retail, Service and Manufacturing). Data are from the ifo Business Survey. Standard errors clustered at the NACE-2 level reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 7: Effect of Working from Home on Severity of COVID-19 Shock – Firm-Level Evidence

	RF		OLS		IV	
	(1)	(2)	(3)	(4)	(5)	(6)
Intensified telework			-15.03***	-7.18***	-77.12***	-38.50***
			(4.71)	(2.48)	(14.06)	(14.25)
WFH feas (z-score)	-12.23***	-4.90***				
	(3.44)	(1.74)				
Mandatory shutdown		41.29***		44.33***		34.72***
		(7.18)		(7.48)		(6.52)
Business outlook 2019Q4						
negative		3.47**		3.69**		2.68*
		(1.41)		(1.42)		(1.45)
positive		0.31		0.65		2.41
		(2.10)		(2.04)		(2.50)
State of business 2019Q4						
negative		11.46***		11.40***		9.76***
		(2.71)		(2.82)		(2.93)
positive		-9.17***		-9.51***		-9.27***
		(2.04)		(2.05)		(1.92)
County F.E.	yes	yes	yes	yes	yes	yes
R^2	0.17	0.26	0.14	0.26		
Wald F					54.17	66.01
Firms	5,850	5,012	5,850	5,012	5,850	5,012

Notes: The dependent variable is an indicator (rescaled by 100) identifying firms who report a "very negative" impact of the COVID-19 crisis in April 2020. *WFH feas* is the z-score (mean 0, standard deviation 1) of the percentage share of employees in the NACE-2 industry with jobs that are feasible for telework (*WFH feas*) as defined in Subsection 2. *Intensified telework* is a binary variable identifying firms who report an intensified usage of telework in response to the COVID-19 crisis in April 2020. Controls include a dummy variable identifying firms operating in a sector subject to mandatory business closures, controls for pre-crisis business conditions and expected future state of business in Q4 2019 (baseline: neutral) and location fixed effects at the county level. Additional controls (not reported) include firm size fixed effects (5 size categories), the share of sales generated abroad, fixed effects for the date of survey completion and survey fixed effects (Construction, Wholesale/Retail, Service and Manufacturing). Data are from the ifo Business Survey. Standard errors clustered at the NACE-2 level reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure 3: SARS-CoV-2 Infections in Germany



Notes: The Figure depicts the distribution of infection rates in % across NUTS-3 regions in Germany for April 15, 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.

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.[17] To minimize measurement issues caused by reporting lags over weekends, we consider weekly data measured on Wednesdays. Our final dataset covers 12 weeks of the pandemic from week 1 (January 23-29, 2020) to week 12 (April 09-15, 2020). Figure 3 plots the distribution of infection rates (cumulative infections/population) across counties and the aggregate number of COVID-19 cases in Germany over the sample time on a log scale. We report summary statistics on infection rates in Table 8.

Table 8: Summary of Infection Statistics at the County-Level

	Mean	Std. Dev.	Min	25th	Median	75th	Max
Infection Rate in %							
on Apr 15, 2020	0.17	0.13	0.02	0.09	0.21	0.21	1.42
on Mar 18, 2020	0.04	0.04	0.00	0.02	0.05	0.05	0.41
Days since first infection							
on Apr 15, 2020	50.7	11.3	33	43	55	55	80

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

[17] In principle, the data also report recoveries but as the exact dates of recovery are difficult to measure and are partly imputed by the local health authorities, we do not use those.

4.2 SARS-CoV-2 Infections, Fatalities and Working from Home – Cross-Sectional Evidence

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 (defined as the cumulative number of cases relative to the number of inhabitants) or fatality rates (defined as the cumulative number of deaths relative to the number of inhabitants) on our regional measures of teleworkability, using the disease data from the last sample week (Wednesday, April 15, 2020).[18] At the regional level, each observation corresponds to an individual county and in most specifications we weight observations according to their population. Re-weighting county-level regressions with population weights gives more importance to larger counties and allows us to recover the conditional mean association between infection rates and telework at the individual level. We regress the infection and fatality rates on our three distinct WFH measures, normalized to z-scores: the share of employees with jobs that are in principle feasible for telework (*WFH feas*), the share of employees that are occasionally (*WFH occ*) and frequently doing telework (*WFH freq*), as previously defined in Subsection 2. We apply a log transformation to the infection rates because the distribution of infection rates is extremely skewed due to the presence of regional infection clusters. We report standard errors that are robust to heteroskedasticity.

The spread of COVID-19 fundamentally depends on the time since the first local infection outbreak because disease dynamics are highly non-linear. We thus control for the number of days since the first infection. To account for transmission of infections from neighboring counties, we control for spatially weighted infection rates in other counties. These are defined as the log-weighted mean of infection rates in other counties, using inverse distances as weights. This accounts for the fact that there is more movement of people and thus higher risk of transmission between geographically closer counties. Furthermore, we include the following set of region-specific socio-economic covariates to control for other factors possibly correlated with infection rates and telework shares: log population, log settled area, log GDP, the fraction of (in- and outward) commuters in the local workforce, the fraction of male population, the fraction of working age population (15-64 yrs.), an infrastructure index that captures reachability of the county by air and weakly rainfall. To construct this last variable, 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. To match weekly infection counts, we compute weekly rainfall by averaging the daily values between consecutive Wednesdays.

Table 9 reports our estimation results. When regressing log infection rates on the WFH measures, we find a negative association between WFH and infection rates across the 401 German counties. Our estimated coefficient of interest is significant at the one-percent level for all WFH measures used in columns (1) to (3) and at the five-percent level if we do not weight counties with their

[18] Results are robust to using earlier weeks. See Table 14 in the Appendix.

Table 9: The Spread of SARS-CoV-2 across Counties and Working from Home

	(1)	(2)	(3)	(4)
WFH measure	*WFH feas*	*WFH occ*	*WFH freq*	*WFH freq*
		Log Infection Rate		
WFH (z-score)	-0.158***	-0.154***	-0.138***	-0.101**
	(0.0487)	(0.0456)	(0.0432)	(0.0417)
NUTS-3 regions	401	401	401	401
		Log Fatality Rate		
WFH (z-score)	-0.368***	-0.351***	-0.298***	-0.224**
	(0.105)	(0.0974)	(0.0933)	(0.0895)
NUTS-3 regions	361	361	361	361
Controls	yes	yes	yes	yes
Population weights	yes	yes	yes	no

Notes: Dependent variables are the SARS-CoV-2 infection rates or fatality rates (in logs) up to April 15, 2020 at the NUTS-3 level based on data from the Robert-Koch-Institut. WFH is the z-Score (mean 0, standard deviation 1) of the percentage share of employees in the county with jobs that are feasible for telework (*WFH feas*) or that are either at least occasionally (*WFH occ*) or frequently (*WFH freq*) doing telework as defined in Subsection 2. Observations correspond to individual NUTS-3 regions (i.e. counties, *Kreise and kreisfreie Städte*) and estimates are weighted based on population size. Controls are region-specific log population, log settled area, log GDP, the fraction of (in- and outward) commuters in the local workforce, the fraction of male population, the fraction of population in working age (15-64 yrs.), an infrastructure index that captures reachability of airports, weekly rainfall, 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. Standard errors are heteroskedasticity robust. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

population size (column 4). According to our baseline estimates in column (3), a one-standard-deviation increase in the share of employees working from home frequently is associated with a 14% lower infection rate. Note that we do not observe the actual fraction of workers who work from home 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. 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 concerns. Instead, the coefficients on the WFH measures can be interpreted as (reduced-form) causal estimates, whose magnitude is plausibly downward biased relative to the true one due to mis-measurement. To illustrate the quantitative implication of the estimates consider the following thought experiment: If Berlin, a county with a rather high share of WFH frequent jobs (z-score of 2.44) had a one standard deviation lower share of such jobs[19] this would imply more than 705 additional cases on top of the actual 5,114 cases that have been reported in Berlin as of April 15, 2020.

Since measurement error caused by regional variation in testing capacities might play a role in observing different infection rates, the lower panel of Table 9 reports the coefficients of our WFH proxies with log fatality rates as the dependent variable.[20] Also in this case the different measures of telework are negative and again significant at the one-percent level or at the five-percent level if we do not weight counties according to their population. A one-standard-deviation increase in *WFH freq* is associated with an almost 30% drop in the fatality rate. Using the same thought experiment as for the SARS-CoV-2 infection rate, the estimated impact of a one-standard-deviation change in WFH on the fatality rate in column (3) translates to more than 30 additional death cases on top of the actually reported 102 cases in Berlin as of April 15, 2020.

As an alternative strategy to address potential measurement error caused by regional variation in testing for COVID-19, we additionally control for regional differences in health care capacities, proxied by the number of hospitals or hospital beds per capita within the county and estimate very similar coefficients.[21] Our coefficient of interest also continues to be significant for all three proxies of WFH when we allow for clustering of standard errors at the more aggregate state (*Bundesland*) level. Finally, as there are 40 counties that experienced no fatalities until April 15, we re-estimate columns (1) - (3) using a Poisson estimator and find the effect of WFH on infections (fatalities) to be significant at the five- (one-) percent level (see Table 15 in the Appendix).

To further assess whether the negative cross-sectional correlation between WFH and coronavirus infections indeed captures reduced contagions at or on the way to the workplace, we interact our WFH measures, alternatively, with regional working-age-population shares or regional employment shares. A larger share of jobs that can be conducted at home should have a stronger impact on SARS-CoV-2 infections in regions where a larger fraction of the population is actually in the labor force. We thus expect a higher WFH share to have a larger impact in regions with a higher share of the population in working age or in employment. Table 10 includes interactions with both measures. The interaction term between the working-age share and WFH in Panel A is negative for all WFH measures. For *WFH feas* and *WFH occ* it is significant at the one-percent level and for *WFH freq* it is significant at the ten-percent level. The direct coefficient of WFH even turns positive in these specifications, suggesting that we find a negative association between WFH and the infection rate only for counties with a sufficiently large working-age population share. It turns out that this is the case for the working-age population shares of 392 out of 401 counties. The interaction term between WFH and regional employment shares is also negative and significant at the one-percent level for all proxies of WFH.

Overall, we take these results as an indication that the negative effect of higher WFH shares on infections indeed operates via a reduction in work-related contacts. We will provide further evidence

[19] Corresponding roughly to numbers for the county Bayreuth (Bavaria).

[20] We observe fatalities in 361 of the 401 counties.

[21] We do not include these covariates in our baseline specification, as we do not observe them for all 401 counties.

Table 10: COVID-19 and Working from Home - Interactions

	(1)	(2)	(3)
	Log Infection Rate		
WFH measure	*WFH feas*	*WFH occ*	*WFH freq*
Panel A:	*Working Age Population Share (%)*		
WFH (z-score) **x Working age**	-0.0211***	-0.0194***	-0.0151*
	(0.00644)	(0.00682)	(0.00815)
WFH (z-score)	1.282***	1.174**	0.893
	(0.445)	(0.470)	(0.561)
Working age	0.0663***	0.0683***	0.0716***
	(0.0140)	(0.0144)	(0.0154)
Panel B:	*Employment Share (%)*		
WFH (z-score) **x Employment**	-0.0195***	-0.0189***	-0.0193***
	(0.00557)	(0.00554)	(0.00593)
WFH (z-score)	0.642***	0.620***	0.645***
	(0.235)	(0.232)	(0.241)
Employment	0.0258*	0.0250*	0.0232*
	(0.0138)	(0.0136)	(0.0136)
Controls	yes	yes	yes
Population weights	yes	yes	yes
NUTS-3 regions	401	401	401

Notes: Dependent variables are the SARS-CoV-2 infection rates (in logs) up to April 15, 2020 at the NUTS-3 level based on data from the Robert-Koch-Institut. WFH is the z-Score (mean 0, standard deviation 1) of the percentage share of employees in the county with jobs that are feasible for telework (*WFH feas*) or that are either occasionally (*WFH occ*) or frequently (*WFH freq*) doing telework as defined in Subsection 2. Panel A includes interactions with the regional percentage share of working age population and Panel B includes interactions with regional percentage employment shares. Observations correspond to individual NUTS-3 regions (i.e. counties, *Kreise and kreisfreie Städte*) and estimates are weighted based on population size. Controls are region-specific log population, log settled area, log GDP, the fraction of (in- and outward) commuters in the local workforce, the fraction of male population, the fraction of population in working age (15-64 yrs.), an infrastructure index that captures reachability of airports, weakly rainfall, 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. Standard errors are heteroskedasticity-robust. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

for this channel when studying the evolution of mobility patterns over time in the following section.

5 SARS-CoV-2 Infections and Working from Home over Time

Next, we aim to further investigate how working from home affects the spread of COVID-19. A central policy question with regard to confinement strategies is whether working from home 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 working from home instead allows for more social distancing even in the absence of confinement.

5.1 Effects of Working from Home on Infections before and after Confinement

To learn more about potentially time-varying effects of working from home on coronavirus infections, we now consider weekly panel data. We observe infection rates for each county over 12 weeks from January 29, 2020 to April 15, 2020 which allows us to estimate how WFH affects infection rates within counties over time using the panel structure of our data. All German federal states simultaneously imposed confinement measures on March 23 in a coordinated way, except for Bavaria, which started confinement already on March 21. Thus, in our data confinement is present during sample weeks 8-12.[22] Specifically, 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[23] and weekly rainfall within the county. The regression specification is given by

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

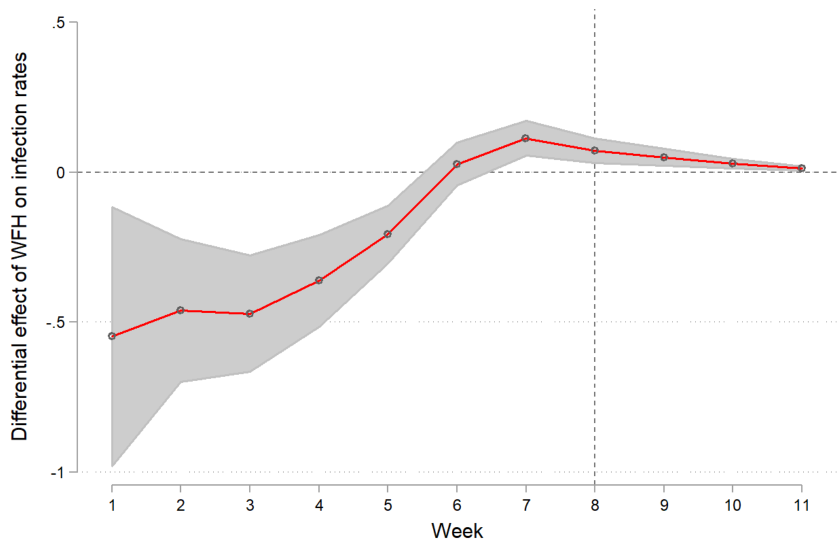
Here $i_{it} = I_{it}/L_i$ is the infection rate (cumulative infections divided by the number of individuals) in county i in period t, β_t captures the week-specific differential effect of *WFH freq* on infection rates, X_{it} is the vector of covariates and δ_i and δ_t are, respectively, county and period fixed effects. We cluster standard errors at the county level. Figure 4 plots the estimated coefficients β_t and the 95-percent confidence band.

The weekly coefficient estimates in Figure 4 suggest that WFH is 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 five-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

[22] See the Appendix A.1 for a description of the confinement measures in Germany.

[23] As before, we define log spatial infection rates as the weighted mean of infection rates in other counties using inverse distances as weights.

Figure 4: The Effect of Working from Home on Infection Rates over Time



Notes: The Figure plots coefficient estimates of $WFH_i \times t$ (using the z-Score of *WFH freq*) on log infection rates by week (week 12 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).

weeks 1-7 are identical to those in weeks 8-11, after confinement rules where implemented by state governments, can be clearly rejected ($F = 28.73$, $p < 0.01$).

In Table 11, we conduct a simple difference-in-differences estimation where we interact our WFH measures with a *pre confinement* dummy that indicates weeks before the confinement (weeks 1-7). Note that the level effect of WFH is absorbed by the county fixed effects. Similarly to the weekly coefficient estimates shown in Figure 4, we find a relatively larger effect of WFH on reducing infection rates before confinement rules came into effect. The interaction terms are negative and significant at the five-percent level or lower for all WFH measures.[24]

We now test if confinement was particularly effective in reducing infection rates in states imposing stricter confinement rules and if there is any interaction between the strictness of confinement and working from home. As the majority of confinement rules were implemented at the state level, there is some regional variation in confinement strictness. In particular, 10 states chose to implement relatively lax confinement rules and 6 states opted for a more strict lockdown. In states with relatively strict confinement, leaving the household was only allowed for certain purposes which included, among others, travel to the workplace. In other states, individuals were allowed to leave their homes freely. The six states imposing stricter rules were Bavaria, Saarland, Saxony, Saxony-Anhalt, Brandenburg and Berlin. Figure 10 in the Appendix plots the differential effect

[24] As these regressions consider within-county variation over time, we do not use population weights here.

Table 11: COVID-19 and Working from Home Pre- and Post-Confinement

	(1)	(2)	(3)
	Log Infection Rate		
WFH measure	*WFH feas*	*WFH occ*	*WFH freq*
WFH (z-score) **x Pre confinement**	-0.0753**	-0.0802***	-0.0728**
	(0.0304)	(0.0298)	(0.0292)
Controls	yes	yes	yes
County F.E.	yes	yes	yes
Week F.E.	yes	yes	yes
Obs.	3,067	3,067	3,067

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 the z-Score (mean 0, standard deviation 1) of the percentage share of employees in the county with jobs that are feasible for telework (*WFH feas*) or that are either at least occasionally (*WFH occ*) or frequently (*WFH freq*) doing telework as defined in Subsection 2. *Pre confinement* is a dummy variable that indicates weeks 1-7. Observations correspond to individual weeks within NUTS-3 regions (i.e. counties, *Kreise and kreisfreie Städte*). 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

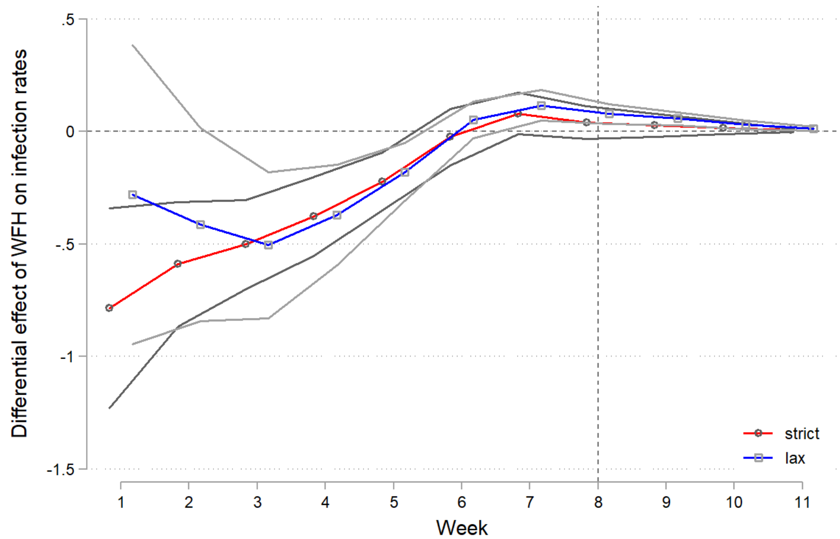
of strict confinement over time. The results show that counties in states with strict confinement rules experienced significantly lower infection rates during weeks 6-10 around the implementation of the confinement. Figure 5 plots the differential effects of WFH separately for states with strict and lax confinement. The estimates suggest that the effectiveness of WFH on infection rates was comparable across both groups of states. In particular, WFH was equally effective in reducing infection rates before the confinement in both groups of states.

5.2 Dynamic Spatial Count Model

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, we now 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.[25]

[25]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.

Figure 5: The Effect of Working from Home on Infection Rates over Time - The Role of Confinement Strictness



Notes: The Figure plots coefficient estimates of $WFH_i \times t$ (using the z-Score of *WFH freq*) on log infection rates by week (week 12 is absorbed by fixed effects) for the group of states with lax and strict confinement rules separately. The dashed vertical line for week 8 indicates the week when the majority of confinement rules where set into force by federal states. The black lines correspond to 95 percent confidence intervals (with clustering at the county level).

This econometric model is significantly more flexible than the linear models we have used above. 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

$$\mu_{it} = e_i \nu_{it} + \lambda Y_{it-1} + \phi \sum_{j \neq i} w_{ij} Y_{jt-1}. \tag{2}$$

Here e_i is the population share of region i, ν_{it} is the endemic mean of the process that depends on county-specific covariates, λY_{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.[26]

The county-specific endemic component is modelled as the product of the county's population share

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

e_i, accounting for regional exposure, and ν_{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:

$$\log \nu_{it} = \beta_0 WFH_i + \beta_1 WFH_i \times Preconf_t + \mathbf{Z_{it}}'\beta^{\nu} + \delta_t + \gamma_1 \sin \omega t + \gamma_2 \cos \omega t. \tag{3}$$

$\mathbf{Z}_{it}$ includes the following controls: log population density, log GDP, the fraction of (in- and outward) commuters in the local workforce, the fraction of male population, the fraction of working age population (15-64 yrs.), an infrastructure index that captures reachability of the county by air and weakly rainfall.

The results for this model are reported in Table 12. 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 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 $WFH_i \times Preconf_t$ is also negative and highly significant, confirming the additional infection-reducing impact of WFH before the confinement from the linear model.[27] The autoregressive coefficient λ is quantitatively large and highly significant, indicating the importance of the epidemic component. Finally, the spatial component ϕ 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.

5.3 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 road mobility patterns within counties during the COVID-pandemic period.[28] As we have seen in Section 3 above, counties or industries with a higher share of WFH jobs also experienced less short-time work applications during the months of March and April.

In order to study the effects of WFH and confinement on traffic movements within a county, we use cell phone tracking data from Teralytics.[29] The company provides anonymized geo-location data of German cell phone users, sourced from the mobile phone carrier Telefónica, which holds

[27] 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 $E(Y_{it}|X_{it}) = \mu_{it} = \exp\left(e_i \nu_{it} + \lambda Y_{it-1} + \phi \sum_{j \neq i} w_{ij} Y_{jt-1}\right)$. 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 $\frac{\partial E(Y_{it}|X_{it})}{\partial WFH_i} = (\beta_0 + \beta_1 \times Preconf_t)\nu_{it} e_i \mu_{it}$.

[28] We also consider commuting traffic by train in the Appendix.

[29] 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.

Table 12: SARS-CoV-2 Infections and Working from Home: Dynamic Spatial Count Model

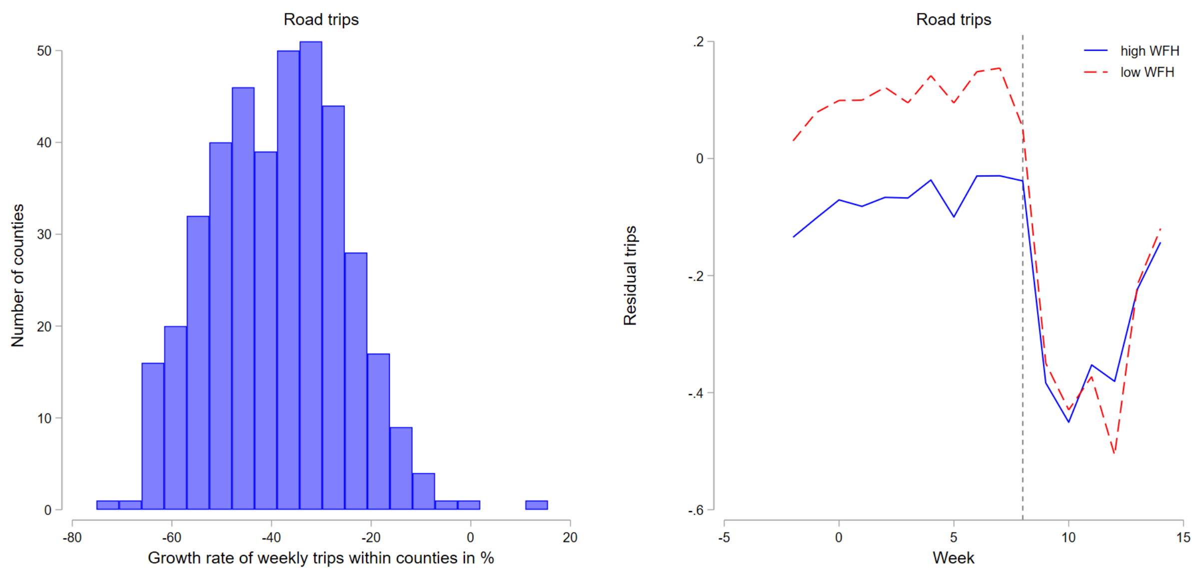
	(1)	(2)	(3)	(4)
	Infections			
	Poisson		*Negative Binomial*	
WFH	-0.0780***	-0.0526***	-0.0797***	-0.0487***
	(0.0086)	(0.0088)	(0.0238)	(0.0258)
WFH × Pre confinement		-0.0491***		-0.0410***
		(0.0041)		(0.0126)
λ	0.7509**	0.7503***	0.7620***	0.7620***
	(0.0041)	(0.0043)	(0.0186)	(0.0186)
ϕ	0.0841***	0.0858***	0.0605***	0.0629***
	(0.0039)	(0.0034)	(0.0091)	(0.0010)
Controls	yes	yes	yes	yes
log L	-20,853	-20,777	-11,637	-11,630
AIC	41,737	41,587	23,306	23,295
Obs.	4,812	4,812	4,812	4,812
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 as defined in Subsection 2. *Pre confinement* is a dummy variable that indicates weeks 1-7. Observations correspond to individual NUTS-3 regions (i.e. counties, *Kreise and kreisfreie Städte*). Columns (1) and (2) report results from a Poisson model, columns (3) and (4) from a Negative Binomial model (Type 1). Controls are region-specific log population density and log GDP, the fraction of (in- and outward) commuters in the local workforce, the fraction of male population, the fraction of population in working age (15-64 yrs.), an infrastructure index that captures reachability of airports, weakly rainfall (columns 2 and 4). The spatial term includes the number of cases in other regions with estimated spatial weights.*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

roughly one third of the German market. Teralytics uses a proprietary algorithm to identify distinct trips and to classify journeys over a distance of more than 30 kilometers by mode of transportation (motorized private transport, train and plane). The data at our disposal contain the total number of trips within a county and between any two counties in Germany on a daily basis since January 2020. Trip measures are based on switches of mobile phone connections between cell towers. Our measure of interest is the log of total weekly road trips by car within counties. 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.[30] The left panel of Figure 6 shows the histogram of growth rates of road traffic at the county level over the same 12 week period that we considered in the infection data (week 1:

[30]The minimum length and distance requirements are imposed by reporting-thresholds in the Teralytics data.

Figure 6: Working from Home and Decline in Regional Mobility



Notes: The left graph of the Figure plots the distribution of 12-week growth rates across counties (from week 1: Jan 23-29, 2020 to week 12: Apr 09-15, 2020). The right graph shows the development of average road mobility (left) 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, log area, share of commuters, share of males, share of working age population and proximity to airports.

Jan 23-29, 2020, week 12: Apr 09-15, 2020). In virtually all counties the number of road trips fell substantially during this period. On average, road traffic within counties fell by 39%. The right panel plots the development of average residual road trips 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 log GDP, log population, log area, share of commuters, share of males, share of working age population and the proximity to airports. 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*.[31]

The time series show that regions with a higher share of teleworkable jobs experience a lower level of traffic before the confinement after controlling for confounding factors. Once confinement rules are implemented in Germany, there is a sudden overall decline in the level of road traffic in both groups of counties. However, while traffic was lower in high WFH counties before confinement, counties experienced a convergence in traffic levels post confinement, so that the drop in the number of road trips was larger in low-WFH regions. One explanation for this convergence in traffic patterns is

[31] A similar pattern is visible when using different cutoff levels for *WFH freq* such as above/below the Median or the top/bottom 10%.

Table 13: Road Trips and Working from Home Pre- and Post-Confinement

	(1)	(2)	(3)
	Log Road Trips		
WFH (z-score)	-0.0361	-0.0108	
	(0.0292)	(0.0296)	
WFH (z-score) × **Pre Confinement**		-0.0438***	-0.0433***
		(0.00722)	(0.00721)
Controls	yes	yes	no
County F.E.	no	no	yes
Week F.E.	yes	yes	yes
Obs.	4,812	4,812	4,812

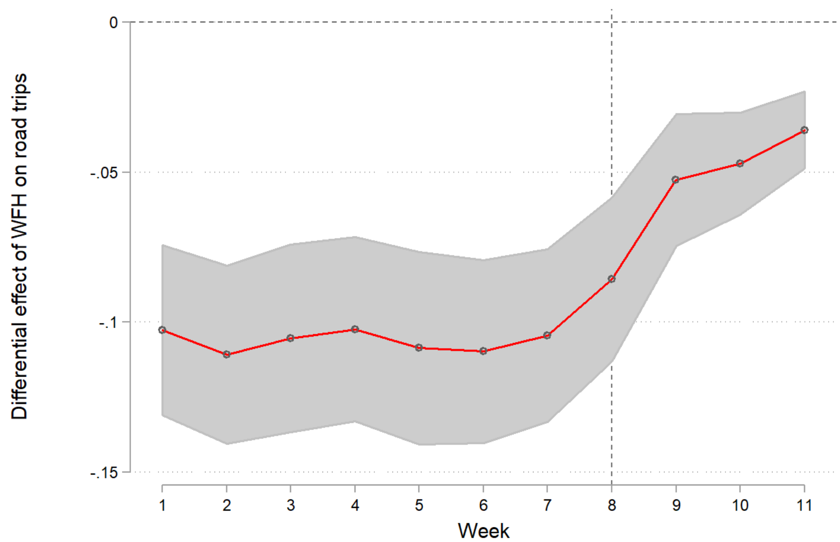
Notes: Dependent variable is the weekly number of road trips within a county during each week (in logs) at the NUTS-3 level based on data from Teralytics (from week 1: Jan 23-29, 2020 to week 12: Apr 09-15, 2020). WFH is the z-Score (mean 0, standard deviation 1) of the percentage share of employees in the county with jobs that are frequently (*WFH freq*) doing telework as defined in Subsection 2. *Pre confinement* is a dummy variable that indicates weeks 1-7. Observations correspond to individual weeks within NUTS-3 regions (i.e. counties, *Kreise and kreisfreie Städte*). Controls are region-specific log GDP, log population, log area, share of commuters, share of males, share of working age population, proximity to airports and weekly rainfall. Standard errors are corrected for clustering at the NUTS-3 county level. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

the previously established association between WFH and short-time work. During the pandemic 30% of employees in Germany were on short-time work. Once a large fraction of workers stay at home independently of whether they work from there, the traffic-reducing effect of WFH becomes irrelevant. This interpretation is supported by the estimation results shown in Table 13. In column (1) we regress the log number of road trips within a county during a week on the z-score of WFH freq. and the same set of controls that we used to compute residual traffic levels. Over the 12-week time window the coefficient of WFH is negative, yet insignificant, suggesting that on average road traffic was not significantly lower in regions with more telework during that time span. When interacting WFH with the pre-confinement dummy in column (2) the picture becomes more nuanced. Before the confinement rules apply, counties with a one standard deviation higher WFH share experienced ceteris paribus about 5% less road traffic per week. This larger effect before the confinement is confirmed in column (3) where we also include county fixed effects. Similar to the empirical infections model, we also estimate weekly coefficients 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, β_t captures the week-specific effect of *WFH freq*, X_{it} is the vector of covariates and δ_i and δ_t are, respectively, county

Figure 7: The Effect of Working from Home on Road Trips over Time



Notes: The Figure plots coefficient estimates of $WFH_i \times t$ (using the z-Score of *WFH freq.*) on log number of road trips by week (week 12 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).

and period fixed effects. The vector of covariates includes weekly rainfall and interactions of week dummies with the share of commuters in the county. Figure 7 plots the estimated coefficients β_t. The Figure confirms that, similarly to the dynamic effects of WFH on infections shown in Figure 4, 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 1-7 are identical to those in weeks 8-11 after confinement was implemented can be clearly rejected ($F = 48.42$, $p < 0.01$). In the Appendix we estimate the same model using traffic from commuter trains as the dependent variable (defined as the number of inbound train trips into the county). Results from these estimates are shown in Figure 11 and qualitatively similar. The null hypothesis can be rejected here at the 5% level ($F = 5.28$).

The observed convergence of mobility over time rationalizes why WFH was particularly effective in reducing infections before the confinement. After the confinement, the reason for staying at home (either due to telework or due to short-time work) became irrelevant for the spread of COVID-19. Of course, the decline in traffic is probably not the sole explanation why the differential effectiveness of WFH in reducing SARS-CoV-2 infections fell over time. Other factors reducing infections at the workplace could have played a role too, in particular measures to increase physical distances between co-workers, stricter hygiene rules or compulsory wearing of face masks.

Summarizing, we find three pieces of empirical evidence supporting the claim that working from home was not complementary to the confinement policies implemented in Germany. First, WFH was particularly effective in the early stages of the pandemic before confinement measures were implemented. Second, there was no difference in the effectiveness of WFH between states with more or less strict confinement rules in place. Third, the level of road traffic activity converged across counties with more or less WFH after confinement rules were implemented. This lets us conclude that working from home and confinement rules were rather substitutes with regard to reducing SARS-CoV-2 infections. This conclusion has important policy implications: as confinement is lifted, working from home should be maintained as much as possible as long as infection risk is present.

6 Conclusions

In this paper we investigated the relationship between workers' ability to work from home during the COVID-19 pandemic, labor-market outcomes and SARS-CoV-2 infections. Using exogenous regional and sectoral variation in working from home ability based on variation in occupational composition, we have first shown that working from home has been an important tool to reduce short-time work applications and mitigating the labor supply shock due to confinement. In a second step, we have studied the effect of exogenous regional variation in working from home ability on SARS-CoV-2 infections and fatalities. We have shown that working from home has been important for reducing infections and fatalities, in particular during the early stages of the pandemic. Working from home has been less important in reducing infections after confinement was imposed by authorities, which is in line with observed mobility patterns from cell-phone tracking data. Overall, confinement and working from home are substitutable policies in reducing infections. This implies that working from home should be encouraged in the post-confinement phase as long as significant infection risk remains present.

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A Appendix

A.1 Description of Confinement Measures in Germany

Confinement: On March 8, federal and state governments recommended the cancellation of all big public events. Governments then agreed on extensive confinement to restrict social contacts on Sunday, March 22. Most of these rules started to apply from the next Monday, March 23 onwards and were planned to stay until May 3-4 (with some regional variation across states: 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. 6 states 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 onwards. Stores providing necessities remained open. Restaurants were free to offer pickup service.

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

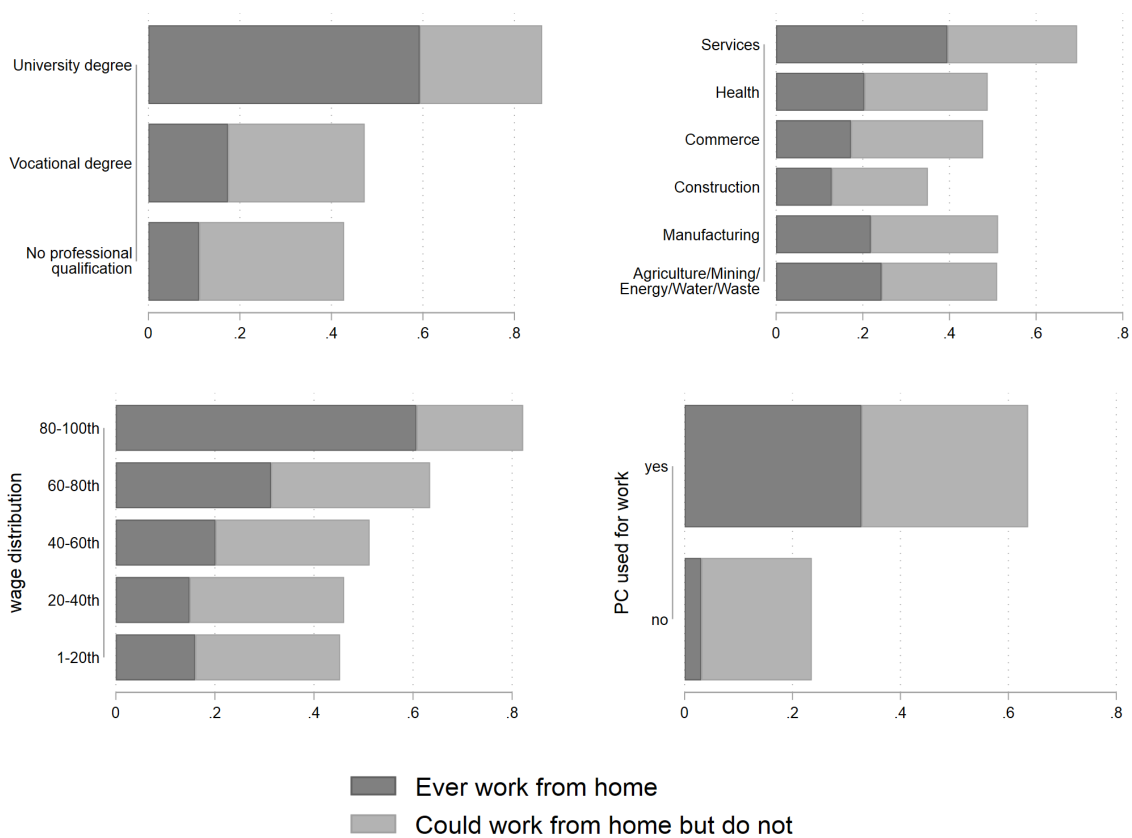
Obligatory Face Masks: From April 27 onwards, wearing a mouth-nose mask during public transport or while buying groceries was mandatory.

Table 14: Robustness: COVID-19 and Working from Home - Earlier Weeks

	(1)	**(2)**	**(3)**
Date	*Apr 01* *Week 10*	*Apr 08* *Week 11*	*Apr 15* *Week 12*
	Log Infection Rate		
WFH (z-score)	-0.0707*	-0.0989**	-0.138***
	(0.0382)	(0.0405)	(0.0431)
NUTS-3 regions	401	401	401
	Log Fatality Rate		
WFH (z-score)	-0.192**	-0.255***	-0.298***
	(0.0869)	(0.0912)	(0.0932)
NUTS-3 regions	341	358	361
Controls	yes	yes	yes
Population weights	yes	yes	yes

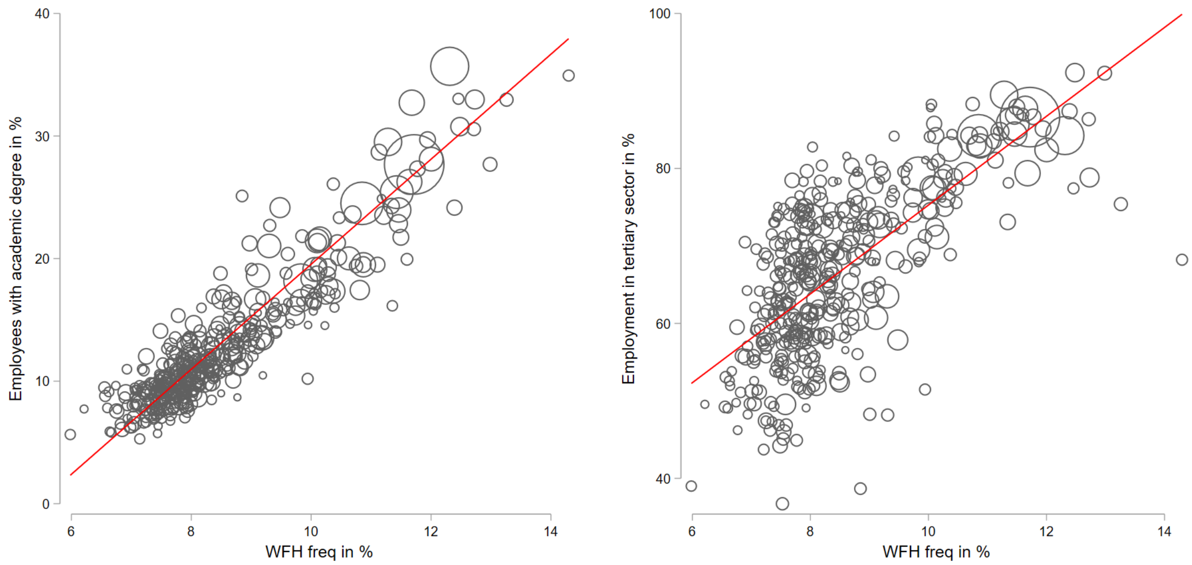
Notes: Dependent variables are the SARS-CoV-2 infection rates or fatality rates (in logs) up to April 1, April 8 or April 15, 2020 at the NUTS-3 level based on data from the Robert-Koch-Institut. WFH is the z-Score (mean 0, standard deviation 1) of the percentage share of employees in the county with jobs that are frequently (*WFH freq*) doing telework as defined in Subsection 2. Observations correspond to individual NUTS-3 regions (i.e. counties, *Kreise and kreisfreie Städte*) and estimates are weighted based on population size. Controls are region-specific log population, log settled area, log GDP, the fraction of (in- and outward) commuters in the local workforce, the fraction of male population, the fraction of population in working age (15-64 yrs.), an infrastructure index that captures reachability of airports, weakly rainfall, 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. Standard errors are heteroskedasticity-robust. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure 8: Pre-Crisis WFH Patterns By Worker Group



Notes: Dark-shaded bars reflect the pre-crisis share of employees who work from home at least occasionally (*WFH occ.*). Light-shaded bars represent the share of employees without WFH experience but with a teleworkable job (corresponding to the difference between *WFH feas.* and *WFH occ.*). The total size of the bars indicate the overall share of jobs which can be done from home at least partly (*WFH feas.*). Data are from BIBB/BAuA Employment Survey 2018.

Figure 9: Correlation Between WFH, Higher Education and Tertiary Employment



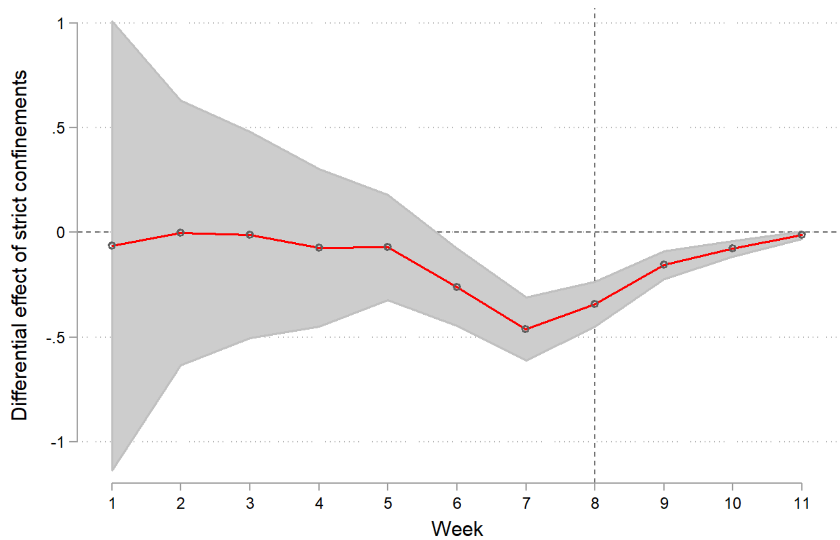
Sources: The figure depicts the linear fit between the share of frequent homeworkers (*WFH freq*) and the share of employees with an academic degree (left panel) and the proportion of employment in the tertiary sector (right panel) across 401 NUTS-3 regions. Counties are weighted with total population. Employment data are from the Federal Employment Agency 2019. Computation of *WFH freq* is based on data from the BIBB/BAuA Employement Survey 2018 and employment statistics of the Federal Employment Agency 2019.

Table 15: The Spread of COVID-19 across Counties and Working from Home – Poisson Estimates

	(1)	(2)	(3)
WFH measure	*WFH feas*	*WFH occ*	*WFH freq*
		Infections	
WFH (z-score)	-0.175**	-0.156**	-0.146**
	(0.0768)	(0.0721)	(0.0639)
		Fatalities	
WFH (z-score)	-0.409***	-0.360***	-0.295***
	(0.126)	(0.119)	(0.104)
NUTS-3 regions	401	401	401
Controls	yes	yes	yes
Population weights	yes	yes	yes

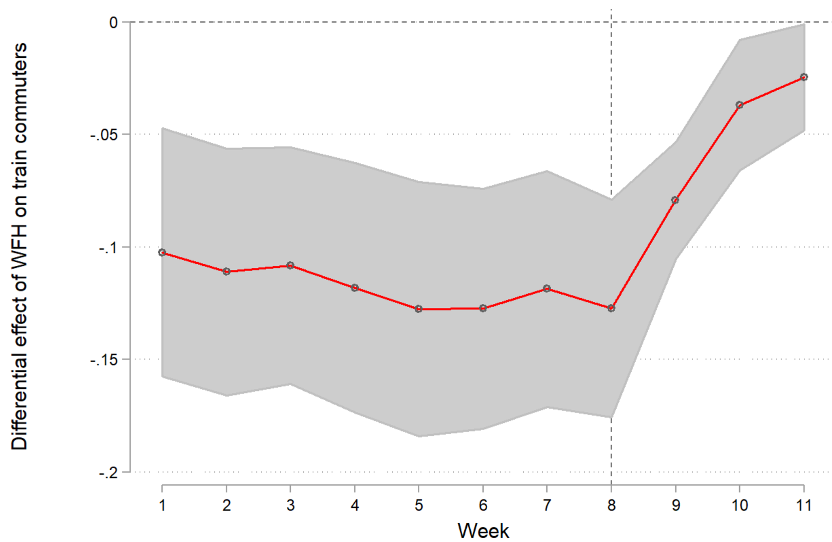
Notes: Dependent variables are the cumulative SARS-CoV-2 infections or fatalities up to April 15, 2020 at the NUTS-3 level based on data from the Robert-Koch-Institut. WFH is the z-Score (mean 0, standard deviation 1) of the percentage share of employees in the county with jobs that are feasible for telework (*WFH feas*) or that are either occasionally (*WFH occ*) or frequently (*WFH freq*) doing telework as defined in Subsection 2. Observations correspond to individual NUTS-3 regions (i.e. counties, *Kreise and kreisfreie Städte*) and estimates are weighted based on population size. Controls are region-specific log population, log settled area, log GDP, the fraction of (in- and outward) commuters in the local workforce, the fraction of male population, the fraction of population in working age (15-64 yrs.), an infrastructure index that captures reachability of airports, weekly rainfall, 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. Estimation results are obtained via Poisson pseudo-maximum likelihood estimation. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure 10: The Effect of Confinement Strictness on Infection Rates over Time



Notes: The Figure plots coefficient estimates of $Strict \times t$ (where $Strict$ is a dummy indicating states with strict confinement rules) on log infection rates by week (week 12 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).

Figure 11: The Effect of Working from Home on Train Commutes over Time



Notes: The Figure plots coefficient estimates of $WFH_i \times t$ (using the z-Score of *WFH freq*) on log number of inbound train trips by week (week 12 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).

Table 16: Description of County-Level Variables

Variable	Description	Source & Reference date
Total population	Number of residents per county	FSO, 31.12.2018
Settled area	Number of residents per hectare of inhabited area	FSO, 31.12.2018
Share of working age population	Number of residents aged 15-64 relative to total population	FSO, 31.12.2018
Share of male population	Number of male residents relative to total population	FSO, 31.12.2018
Share of elderly population	Number of residents aged 74 and older divided by total population	FSO, 31.12.2018
Share of commuters	Number of in- and outward commuters relative to number of employed residents	BA, 30.06.2019
Reachability of nearest airport	Average travel time by car to the nearest international airport	BBSR, 2018
Share of STW registrations	Number of persons mentioned in applications for short-time work in March and April 2020 relative to total employment in June 2019	BA
Share of employment by sector	Percentage of employment in NACE sections I, C, G and K, respectively	BA, 30.06.2019
GDP	Gross domestic product in TEUR per county	FSO, 2017
Labor productivity	Gross value added in TEUR in 2017 divided by total employment in June 2019	FSO & BA
COVID-19 infections and fatalities	Number of registered infections or fatalities per week	RKI, 23.01.-15.04.2020
Precipitation	Interpolated daily precipitation height, averaged by week	DW, 2020
Hospital beds	Total number of hospitals beds per county	FSO, 2017
Hospitals	Total number of hospitals per county	FSO, 2017

Notes: 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; DW = German Weather Service (*Deutscher Wetterdienst*).

Table 17: WFH Shares by Occupation

	Occupations (KldB 2010 2-digit)	WFH freq	WFH occ	WFH poss
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 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*). See Section 2 for details. Data are from the 2018 BIBB/BAuA Employment Survey.

Table 18: Accounting for Demand Shocks: Intensified Telework Due to COVID-19 and WFH Potential – Firm-Level Evidence

	(1)	(2)	(3)	(4)
WFH freq (z-score)	9.66***			
	(0.85)			
WFH occ (z-score)		11.26***		9.58***
		(1.96)		(1.69)
WFH feas (z-score)			12.08***	
			(1.41)	
WFH unexploited (z-score)				3.85***
				(1.22)
Mandatory shutdown	-24.28**	-19.86**	-17.72**	-17.82**
	(9.47)	(7.99)	(7.17)	(7.24)
Business outlook 2019Q4				
negative	-2.36*	-2.10	-1.66	-1.71
	(1.25)	(1.28)	(1.30)	(1.30)
positive	3.99**	4.06**	4.23**	4.19**
	(1.70)	(1.75)	(1.78)	(1.76)
State of business 2019Q4				
negative	-2.12	-2.11	-2.05	-2.04
	(1.54)	(1.56)	(1.56)	(1.56)
positive	1.61	1.04	0.91	0.91
	(1.90)	(1.79)	(1.68)	(1.70)
Demand drop	-3.78*	-2.80	-2.23	-2.31
	(2.12)	(2.03)	(1.94)	(1.93)
County F.E.	yes	yes	yes	yes
R^2	0.33	0.34	0.34	0.35
Firms	4,536	4,536	4,536	4,536

Notes: The dependent variable is an indicator (rescaled by 100) identifying firms who report an intensified usage of telework in response to the COVID-19 crisis in April 2020. WFH is the z-score (mean 0, standard deviation 1) of the percentage share of employees in the NACE-2 industry with jobs that are feasible for telework (*WFH feas*) or who either occasionally (*WFH occ*) or frequently (*WFH freq*) work from home as defined in Subsection 2. The variable *WFH unexploited* represents the share of workers with a teleworkable job but without any previous remote working experience. Controls include a dummy variable identifying firms operating in a sector subject to mandatory business closures, controls for pre-crisis business conditions and expected future state of business in Q4 2019 (baseline: neutral), a dummy for firms who indicated that the crisis negatively affected demand and location fixed effects at the county level. Additional controls (not reported) include firm size fixed effects (5 size categories), the share of sales generated abroad, fixed effects for the date of survey completion and survey fixed effects (Wholesale/Retail, Service and Manufacturing). Data are from the ifo Business Survey. Standard errors clustered at the NACE-2 level reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 19: Accounting for Demand Shocks: Effect of WFH on STW and COVID-19 Shock – Firm-Level Evidence

	Short-Time Work			COVID-19 Impact		
	(1) RF	(2) OLS	(3) IV	(4) RF	(5) OLS	(6) IV
Intensified telework		-4.03**	-45.01***		-7.25***	-35.87***
		(1.99)	(12.38)		(2.53)	(11.87)
WFH feas (z-score)	-5.44***			-4.48***		
	(1.44)			(1.44)		
Mandatory shutdown	21.08***	25.54***	13.10**	34.77***	37.25***	28.64***
	(4.98)	(5.18)	(5.86)	(6.53)	(6.72)	(5.58)
Business outlook 2019Q4						
negative	-3.66*	-3.23	-4.40**	1.38	1.56	0.50
	(2.08)	(2.18)	(2.07)	(1.55)	(1.57)	(1.66)
positive	1.05	1.13	2.96	1.26	1.55	2.82
	(2.11)	(2.09)	(2.09)	(2.02)	(1.99)	(2.28)
State of business 2019Q4						
negative	10.42***	10.61***	9.50***	8.42***	8.42***	7.29**
	(1.71)	(1.78)	(2.01)	(2.88)	(2.99)	(3.11)
positive	-8.01***	-8.40***	-7.60***	-7.38***	-7.66***	-7.24***
	(1.79)	(1.86)	(1.94)	(1.75)	(1.75)	(1.82)
Demand drop	27.58***	28.01***	26.58***	24.98***	25.22***	24.53***
	(2.57)	(2.53)	(2.33)	(3.04)	(2.99)	(2.86)
County F.E.	yes	yes	yes	yes	yes	yes
R^2	0.27	0.26		0.31	0.31	
Wald F			73.22			75.40
Firms	4,536	4,536	4,536	4,010	4,010	4,010

Notes: The dependent variable in columns 1-3 is an indicator (rescaled by 100) identifying firms who participated in the Short-Time Work scheme due to the COVID-19 crisis in April 2020. The dependent variable in columns 4-5 is an indicator (rescaled by 100) identifying firms who report a "very negative" impact of the COVID-19 crisis in April 2020. *WFH feas* is the z-score (mean 0, standard deviation 1) of the percentage share of employees in the NACE-2 industry with jobs that are feasible for telework (*WFH feas*) as defined in Subsection 2. *Intensified telework* is a binary variable identifying firms who report an intensified usage of telework in response to the COVID-19 crisis in April 2020. Controls include a dummy variable identifying firms operating in a sector subject to mandatory business closures, controls for pre-crisis business conditions and expected future state of business in Q4 2019 (baseline: neutral), a dummy for firms who indicated that the crisis negatively affected demand and location fixed effects at the county level. Additional controls (not reported) include firm size fixed effects (5 size categories), the share of sales generated abroad, fixed effects for the date of survey completion and survey fixed effects (Wholesale/Retail, Service and Manufacturing). Data are from the ifo Business Survey. Standard errors clustered at the NACE-2 level reported in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$