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Firm Digitalisation and Mobility – Do Covid-19-Related Changes Persist?

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Firm Digitalisation and Mobility – Do Covid-19-related Changes Persist?

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Abstract

The Covid-19 pandemic has sparked hope that firm digitalisation will result in long-lasting reductions in mobility and related carbon emissions via the use of working from home and online services. In this study, we quantify the extent to which firm digitalisation can be associated with changes in mobility during the Covid-19 crisis in Germany, both when strong restrictions were in place and after the restrictions were lifted. To this end, we employ a novel text-mining approach to measure digitalisation based on firm websites. We aggregate our firm digitalisation indicator at the district level and link it to changes in mobility between January 2020 and December 2022. Our results indicate that districts with a higher level of firm digitalisation experienced a stronger reduction in mobility during the first two years of the pandemic. However, mobility almost came back to pre-crisis levels after most restrictions were lifted, suggesting that environmental improvements are not long-lasting.

Keywords: Covid-19, digitalisation, mobility reductions, environmental improvements.

JEL codes: H12, I12, L96, O18.

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1. Introduction

The adverse environmental impacts associated with transportation have continuously increased in recent decades and transportation accounted globally for about 23% of total energy sector's direct carbon emissions in 2019, with passenger cars being responsible for a large proportion thereof (IEA, 2022). In 2020, however, the Covid-19 pandemic fundamentally interrupted mobility patterns. In order to prevent infections, digital technologies have been widely leveraged to avoid physical contact. For instance, remote access and virtual meetings allowed employees to work from home (WFH) and online shopping and delivery services enabled customers to purchase goods without leaving the house. Empirical evidence by Alipour et al. (2021) and Alcedo et al. (2022) indicates that these behavioural changes can be linked to lower levels of mobility around the beginning of the crisis. The observed decline sparked hope that the intensified use of digital technologies will result in persistent mobility reductions and a long-run decrease in associated carbon emissions. Comprehensive evidence on the relationship between digitalisation and mobility changes over the entire course of the pandemic, however, is missing. This study aims to close this research gap and quantifies the extent to which firm digitalisation effectively contributed to mobility reductions throughout the pandemic, covering the time frame from January 2020 until December 2022.

The long-term effects of the initial Covid-19 shock are not clear a priori. On the one hand, substantial investments in digital infrastructure and human capital, technological innovation, as well as a persistent increase in WFH arrangements give reason to believe that reductions in mobility are long-lasting (Barrero et al., 2021; Bloom et al., 2021; Bachelet et al., 2022; Erdsiek and Rost, 2022). On the other hand, after the initial Covid-19 shock, social isolation and physical inactivity while working from home may have been compensated by social meetings and an increase in mobility during leisure time. In particular, such compensatory behaviour may have been amplified by the decreasing severity of the pandemic and the lifting of restrictions in 2022. Also, working from home and improved access to services online increased the incentive to move further away from commercial districts, where rents are cheaper, potentially resulting in fewer trips taken but longer distances travelled (Marz and Şen, 2022).

For our analysis, we make use of unique, web-scraped firm-level data for Germany, a large European country with an average level of digitalisation among EU countries (e.g., European Commission, 2022). Moreover, we concentrate on firm digitalisation, which we approximate by estimating the extent to which firms communicate about digital topics on their websites. To this end, we apply a novel text-mining approach based on transfer learning.[1] The indicator has the advantage that it contains, on the one hand, information on online and delivery services and, on the other hand, information relating to firms' potential of offering WFH, since it is likely that more tasks can be carried out remotely if firms have a high level of digital proficiency. Shortly before the start of the pandemic, we predicted the level of digitalisation for all 750,000 firms whose website addresses were available in the Mannheim Enterprise Panel (MUP).[2] The prediction was repeated in December 2022 based on 1,300,000 firms. For our analysis, we average firm-level predictions for German districts ("Kreise") to approximate the local economy's level of digitalisation. Furthermore, we use mobile network data to measure daily changes in mobility over the observed time frame (e.g., Persson et al., 2021).

We use an event study approach based on a difference-in-differences design to analyse how the link between mobility and firm digitalisation evolves over the course of the pandemic. Our regression results indicate a significant decrease in mobility associated with firm digitalisation for the time after the first lockdown up until the end of most Covid-19 restrictions in March 2022. After the lifting of most restrictions, however, ICT-related mobility reductions are no longer significant. The main contribution of our study is, thus, twofold. First, we show that firm digitalisation can indeed be leveraged to reduce physical travel during times of severe health threats. Secondly, however, if health threats and government restrictions ease up, the potential of digital technologies to reduce overall mobility is hardly exploited. This holds, even though factors that facilitate the substitution between physical travel and remote work or online services greatly improved during the pandemic. Hence, we cannot confirm long-term changes in mobility behaviour that might result in environmental improvements. Our results withstand an extensive set of robustness tests. We also contribute to the literature by using a novel text-based measure to approximate firm digitalisation and are able to cover a much longer time frame than previous studies analysing the effects of the Covid-19 crisis.

[1] See Axenbeck and Breithaupt (2022) for a detailed description of the method.

[2] The MUP is the most comprehensive micro database of German firms besides the official business register, which is not publicly accessible.

The remainder of this paper is structured as follows: In Section 2, we summarise related literature and derive our research question. In Section 3, we explain the data as well as the applied transfer learning approach. In Section 4, we present descriptive insights and in Section 5 econometric results. Section 6 includes robustness checks. In Section 7, we discuss our findings and conclude.

2. Related Literature

Whether telecommunications and travel are complements or substitutes has been a subject of intense debate for several decades (e.g., Kraemer, 1982; Mokhtarian, 1990). According to Kraemer and King (1982), telecommunications-transportation substitution depends on certain factors, such as transportation costs and the quality of telecommunication technologies. In contrast, Salomon (1986) puts forward the hypothesis that human beings have an intrinsic need for mobility, and thus travelling is unlikely to decline due to new technological opportunities, rather mobility patterns will change.

A strand of the empirical literature on ICT-enabled mobility reductions focuses on telecommuting. Remote work is highly relevant for the overall environmental debate, as a large proportion of the daily distance travelled is for work, and most people use their car to get there.[3] Conducting a meta-analysis of 39 empirical studies, Hook et al. (2020) find that the large majority of studies observe environmental improvements associated with telecommuting, which are mainly driven by a reduction in work-related trips. Considering also non-work travel, however, Wöhner (2022) only observes mobility savings for people that fully work remotely. People who only partly work from home completely offset saved commutes by an increase in non-work travel.

In most countries, working from home was only occasionally practised until the start of the Covid-19 pandemic, when the number of people working from home tremendously increased. For instance, the share of employees that fully work from home grew from 4 to 27% during the first lockdown in Germany (Emmler and Kohlrausch, 2021). In addition, by June 2020, the share of firms using WFH increased from 48 to 74% in service industries and from 24 to 46% in the manufacturing sector (Erdsiek, 2021). Similarly, Brynjolfsson et al. (2020) find that regions with a higher share of employment in information work were more likely to shift towards WFH. Moreover, Alipour et al. (2021) confirm for the first weeks of the pandemic that a district's WFH

[3] For instance, between 27 and 47% of the daily distance travelled of employees in EU member states is for the purpose of work (Eurostat, 2021); in EU countries, such as Germany and France, roughly two third of all workers use the car to get to their workplace (Destatis, 2021; Insee, 2021).

potential can indeed be associated with overall mobility reductions, but only shortly before the first lockdown was put in place. Using the Global Survey of Working Arrangements, Aksoy et al. (2023) estimate that WFH approximately saved two hours of commuting per worker each week during the pandemic and will save one hour on average each week after the end of the pandemic. Bachelet et al. (2022) calculate for Germany that if 15% of all full-time employees in Germany will continue to work from home, 3% of carbon emissions attributed to the transport sector could be saved.

Besides WFH, online shopping may improve environmental outcomes. In theory, e-commerce can lead to mobility reductions, as orders can be consolidated and distributed more efficiently (e.g., Siikavirta et al., 2002; Durand and Gonzalez-Feliu, 2012; Wiese et al., 2012).[4] For example, Siikavirta et al. (2002) estimate that the maximum greenhouse gas emissions saving potential of e-grocery home delivery services is roughly between 0.3 and 1.3% for Finland. Using empirical data, Jaller and Pahwa (2020) find for Dallas and San Francisco that e-commerce has cut vehicle miles travelled by 7% on average in 2016, but highlight that environmental improvements depend on the modal split and are lower if people visit commercial districts by foot, bike, or public transportation instead of using the car (cf. Durand and Gonzalez-Feliu, 2012; Wiese et al., 2012).

In contrast to WFH, online spending already substantially grew before the Covid-19 crisis (e.g., Alcedo et al., 2022). Nonetheless, the share of online spending in total consumer spending extremely increased at the beginning of the pandemic, jumping from roughly 17% to above 35% during the first two lockdowns. In mid-2022, however, the share of online revenue declined but remained above the pre-crisis level at roughly 24% (Alipour et al., 2022).[5] Moreover, Alcedo et al. (2022) find for the first phase of the pandemic that online spending is positively linked to Google's index of residential activity at the country level, i.e., the approximated relative time spent at home, but the correlation declined until mid-2021.

In addition, empirical evidence shows that digitalisation supports firm resilience during economic crises (e.g., Bertschek et al., 2019; Reveiu et al., 2022). With respect to the Covid-19 crisis, Ben Yahmed et al. (2022) find that a region's digital capital relates to a lower level of short-time work usage at the beginning of the crisis. Also, firms in countries with a better digital

[4]Please note that we refrain from discussing further consequences for the environment of e-commerce that result, for instance, from frequent returns or additional packaging.

[5]Also, absolute online revenue increased during the first two years of the pandemic (bevh, 2022), indicating that the relative increase in online spending did not solely happen due to a decline in offline sales, but there must have been an additional shift towards online commerce.

infrastructure had comparatively higher revenue in 2020 (Doerr et al., 2021). Comin et al. (2022) confirm that technological sophistication can be associated with higher sales at early stages of the crisis. Bertschek et al. (2022) show that the self-employed whose businesses were highly digitalised, benefited much more from the state aid provided by the German government during the pandemic compared to those whose businesses were less digitalised. By analysing World Bank data, Cariolle and Léon (2022) as well as Wagner (2021) show that having a website is related to firm survival during the pandemic. Moreover, Cariolle and Léon (2022) find that having a firm website is positively correlated with strategies that helped to cope with Covid-19 restrictions, such as home-delivery services, online sales, and remote work. Also, Bai et al. (2021), who observe that firm-level WFH feasibility can be associated with higher sales, net income, and stock returns during the pandemic, highlight the complementarity between digital technologies and WFH practices.

Although there are some insights into how digital strategies helped firms during the crisis, comprehensive empirical evidence is missing that accurately quantifies the extent to which firm digitalisation has effectively contributed to mobility reductions over the course of the pandemic, and, most importantly, whether changes have been sustained after most restrictions were lifted. Persistent reductions may exist because factors determining the substitutability between telecommunications and transportation greatly improved in order to cope with the pandemic (cf. Kraemer and King, 1982), such as the technical quality of online communication due to large investments into digital infrastructure and a pandemic-driven surge in technological innovations (Barrero et al., 2021; Bachelet et al., 2022). For instance, the share of new patent applications that support WFH technologies more than doubled from January to September 2020 (Bloom et al., 2021). Moreover, geopolitical instability in Europe has driven gasoline prices extremely high in 2022, providing an additional incentive to replace fuel-based travel with digital solutions.[6] The assumption of long-lasting mobility reductions is supported by surveys as well. These confirm that the share of people working from home did not largely decline after the pandemic became less severe in March 2022 (ifo Institute, 2022; Aksoy et al., 2022).[7] They also show that many customers anticipate doing more online shopping after the pandemic than before (Shaw et al., 2022).

[6] See `https://www.dashboard-deutschland.de` [online; accessed on 5 Jan 20023].

[7] The Google COVID-19 Community Mobility Trends indicator suggests as well that less people visited their workplace after the pandemic than before (see `https://ourworldindata.org/covid-google-mobility-trends` [online; accessed on 5 Jan 2023]).

However, in the light of an intrinsic human need for travel (cf. Salomon, 1986), there is reason to believe that increased remote work and improved online access to services and products do not necessarily result in permanent mobility reductions. For instance, as people have social and self-realisation needs, they may have enhanced social interaction after work over the course of the pandemic, especially after the crisis became less severe in March 2022 and the need to avoid physical contact declined.

Furthermore, WFH increases the difficulty of managerial control (Felstead et al., 2003) and the stigma that people work less (efficiently) when they work remotely may not have diminished as much as expected during the pandemic. For instance, results from a questionnaire-based survey indicate that more than half of the firms did not noticeably change their assessment of remote work productivity (ZEW Mannheim, 2022). As a consequence, employers still may prefer on-site or hybrid work arrangements because both facilitate monitoring employees as well as interaction. It could also be that a lack of supervision has the opposite effect, i.e., individuals who work from home are more efficient in order to work fewer hours. However, the resulting spare time may, in turn, also increase mobility.

In addition, working from home and increased access to online services may incentivise people to move further away from commercial districts, where rents are cheaper. This phenomenon can lower or even offset mobility reductions, as people may travel less often but longer distances (Marz and Şen, 2022). Moreover, if workers are allowed to work remotely they usually can work from everywhere. Hence, long-distance trips, e.g., at weekends, become more appealing as it is possible to work while travelling. Finally, even though studies indicate that individuals buy more often products online than before the pandemic (Alipour et al., 2022; Shaw et al., 2022), people may prefer hybrid shopping modes and search for products offline and only buy them online.

Hence, whether a relationship between digitalisation and mobility reductions during different phases of the pandemic exists is a priori unclear. Therefore, this study analyses how the link between firm digitalisation and changes in mobility evolved over time in comparison to the pre-crisis level. In particular, we aim to shed light on whether changes in mobility persist after the lifting of most Covid-19 restrictions.

3. Data

For our analysis, we combine several data sources at the district level, which are all listed in Table A.1 in the Appendix.

3.1. Mobility

We use mobile network data provided by the German Federal Statistical Office (Destatis) for 400 German districts between January 2020 and December 2022 (Destatis, 2023*c*).[8] The data stem from the Telefónica network and is processed by the company Teralytics before being forwarded to Destatis. Mobility is measured by the number of switches between mobile network cells per device within one district.[9] The *change in mobility* (in %) is our variable of interest and captures the difference between mobility on a given day to the monthly average mobility in 2019 for the same weekday. For instance, switches between cells on the first Monday in September 2020 are compared to the average switches between cells on all Mondays in September 2019. We observe mobility changes for the entire day as well as for daytime and nighttime separately (6 a.m. to 10 p.m. and 10 p.m. to 6 a.m.).

The use of mobile network data has the advantage that it allows measuring mobility within precise, short time intervals. Nonetheless, we would like to acknowledge some of the shortcomings of our mobility indicator. For instance, it should be noted that the Telefónica network does not cover the entire mobile network market. As a result, we only observe changes in mobility for approximately one third of the German population, with varying market shares at the district level. To address this limitation, the data provider extrapolates the data to ensure representativeness (Destatis, 2023*c*). Furthermore, mobile network cells have an average size of 2.8 km to 4.8 km in rural areas and 0.7 km to 1.9 km in urban and suburban areas (Stobbe et al., 2023). Since changes in mobility can only be detected when there is a switch between mobile network cells, it is important to acknowledge that we are unable to observe a large portion of trips that are below these thresholds. Before the pandemic, however, the average distance travelled per day was 46 km, with an average distance of 12 km for a single trip (infas, 2018). Therefore, we assume that we capture the majority of the daily distance travelled and consider this as a minor issue. One further limitation is that mobile network cells differ in size. The size mainly depends on population density since each cell can only handle a certain number of users. This makes it more difficult to capture changes in short distance trips in rural areas. To address this limitation, we control for the average population density and network quality in a district as well as for whether a district is a city ("Stadt") or a countryside area ("Landkreis"). It is also worth noting that rural travel generally involves longer distances, which mitigates this limitation

[8] Please note that we consider "Wartburgkreis" and "Eisenach" as one district.

[9] In addition to mobile phones, also tablets, laptops, and vehicles can have SIM cards, which are removed from the analysis by approximation to avoid double counting.

(infas, 2018). Additionally, most of the German population lives in urban or suburban areas. As we weight our data based on population size, we further reduce the impact of this limitation.[10]

3.2. Firm Digitalisation

To measure firm *digitalisation*, we take advantage of the fact that nowadays a large share of firms have a website, which usually provides insights into a firm's use of digital technologies, such as online shops, digital products, and social media. We collect these insights using a two-step transfer learning approach. The procedure is thoroughly described in the paper "Measuring the Digitalisation of Firms – A Novel Text Mining Approach" by Axenbeck and Breithaupt (2022).

Firstly, we train a text-based machine learning model that allows for automatically determining whether a text contains content on digitalisation. For this purpose, we exploit news articles, as we can easily identify whether they deal with digitalisation topics.[11] This is because news articles appear within clearly defined sections, such as "business" and "politics". Also, news outlets can create special sections if a current topic is particularly relevant, such as "the digital transformation". We use these section titles as labels for supervised machine learning. Online articles have the additional advantage that their HTML code includes keywords for search engine optimisation (SEO), which also relate to the overarching subject of an article. Accordingly, we label all news articles appearing in a section about digitalisation or having the SEO keyword 'digital' embedded in their HTML code as digital and all other articles as non-digital.[12] Based on the annotated newspaper corpus, we train a supervised machine learning model that allows for predicting whether a text is about digitalisation.[13] Secondly, we apply the fitted model to German firms, estimating the likelihood that their website text is about digitalisation. This is the transfer learning step of our text mining approach. The result is a continuous indicator measuring a firm's degree of digitalisation between zero and one. The entire procedure is illustrated in Figure 1.

[10]It is possible that decisions for WFH and e-commerce are different in rural areas than in urban areas because of the greater distances that have to be travelled. However, due to the different mobile network cell sizes, we refrained from heterogeneity analyses that address this difference, as the described measurement problems could strongly distort the result here. However, since longer distances are travelled in rural areas, and mostly by car, mobility reductions presumably lead to greater carbon emission savings here. For this reason, it would be beneficial for future research to investigate whether there are differences between urban and rural areas in terms of how digital technologies impact mobility changes.

[11]We use news articles from a large German newspaper corpus, which is described in detail in Axenbeck and Breithaupt (2022).

[12]Moreover, we only consider articles before 2020, as articles related to the Covid-19 crisis might bias later firm-level predictions.

[13]To this end, we use a Random Forest regression model suggested by Breiman (2001).

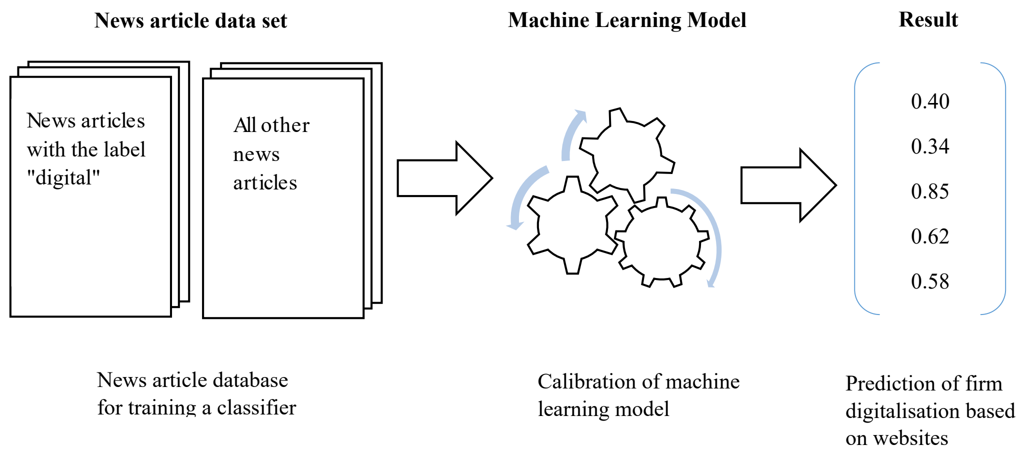

Figure 1: **Transfer learning approach for measuring firm digitalisation.** News article data with binary labels (left), machine learning model (middle), and continuous firm digitalisation scores based on scraped websites (right). Illustration from Axenbeck and Breithaupt (2022).

We retrieve website addresses (URLs) from the Mannheim Enterprise Panel (Bersch et al., 2014). Using all available URLs and the ARGUS Web Scraping Tool (Kinne and Axenbeck, 2020), we scraped 740,875 firm websites in January 2020 as part of the TOBI project.[14] Additionally, we collected information on 1,257,832 firm websites in December 2022 in order to have information covering the end of the observed time frame. In both years, we scraped up to 50 subpages of a firm website. As Kinne and Axenbeck (2020) show that the median number of subpages of a firm website is 15, we consider this threshold to be sufficient.

After applying the machine learning model to firm websites, we average and standardise predictions (mean zero and unitary standard deviation) for all firms in a district for both scraping periods, respectively. Regional distributions are displayed in Figure 2. It is apparent that firms in western Germany are more digital than those located in the eastern part of the country, which is plausible for historical reasons. Moreover, average firm digitalisation only slightly changed between both scraping periods.[15]

Despite small changes, we consider firm digitalisation in levels and do not focus on the effect of

[14] A research project on the potential of firm websites to measure technological progress funded by the German Federal Ministry of Education and Research (funding ID: 16IFI001).

[15] The Pearson correlation coefficient between both periods is 0.85.

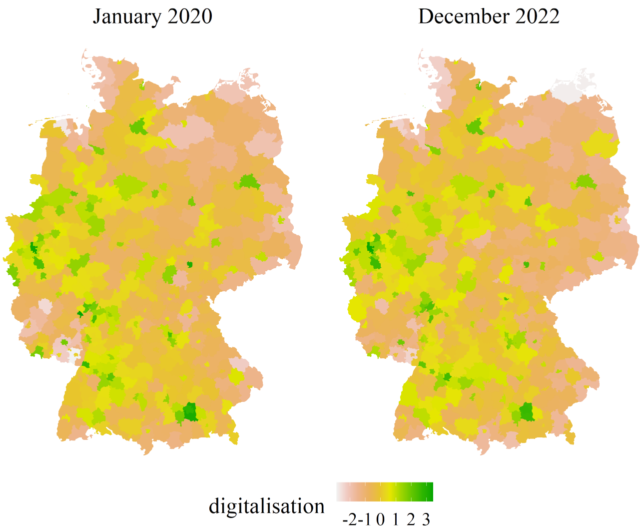

Figure 2: **Regional distribution in January 2020 and in December 2022 of the web-based firm digitalisation indicator.** Values are standardised (mean zero and unitary standard deviation).

changes in firm digitalisation over time in our main analysis. We do this for two reasons. Firstly, we face the issue that the scraping software has changed within the observed time frame, which affects the scale of the indicator and we cannot reliably compare changes. The second reason why we cannot simply compare the change in average firm digitalisation per district between both scraping periods is that the number of available firm websites notably grew.[16] In a robustness check in Section 6, we present a potential approach on how to consider the growing number of firm websites when analysing changes in firm digitalisation at the district level. The changing number of firms with a website also points us to the fact that we only observe the degree of digitalisation for firms that have a website. We address this issue in the same robustness check. Besides, a further minor issue is that most online services are available nationwide. However, we mostly observe small and medium-sized enterprises in our sample and it is likely that their online services are rather locally relevant, even though they are available across district borders.

[16]The increase in available firm websites may have been due to more research effort being put into identifying web addresses by the data provider or because the number of firms that have a website has increased. Presumably, both factors played a part, but we assume the second reason had a larger impact, since establishing a firm website helped sustain business during the pandemic.

3.3. Control variables

Furthermore, as changes in mobility and firm digitalisation can be simultaneously affected by several factors, we add a broad variety of control variables.

We include two control variables relating to the *pandemic situation*. Firstly, we consider the *weekly* number of Covid-19 *cases* per 100,000 inhabitants as a rolling window. Secondly, we add an index that captures the severity of *containment measures* in each district on a given day. Moreover, we account for *socioeconomic* characteristics that may explain adherence to containment measures by including information on the *share of academics*, the *GDP per inhabitant*, the fraction of *low-income households* ($\leq$ €1000 per month), the number of *people on social benefits*, and *the share of people* that work *in the service sector*. Also, a district's *infrastructure* may impact the measurement of mobility as well as actual mobility changes and the location choice of digital firms. Therefore, we add information on *cars per person*, the share of households with a broadband availability of at least 50 *Mbit/s*,[17] and the area in a district that is either *not covered by all* network providers or *not covered* by any network provider in %. Also, *demographic characteristics* may be relevant for the link between mobility and firm digitalisation, such as the *share of men* in a district, the population that is *not of working age*, the *number of inhabitants* as well as *changes in* the *population*, *population density*, *changes in* the number of *in-commuters* and *out-commuters* as well as the number of *one-person households* and the *living space per household*. Last but not least, we control for *geographic* characteristics by adding a dummy which is one if a district represents a *city* and is zero otherwise as well as a dummy that captures whether a district is located in former *West* or East *Germany*. Most of the control variables are observed only once.

4. Descriptive Insights

In the following, we provide descriptive insights into the relationship between firm digitalisation and changes in mobility, measured as the difference between mobility on a given day and the average monthly mobility in 2019 on the same day of the week.

[17]Please note that broadband availability is either a crucial control variable, as it might be in fact household digitalisation and not firm digitalisation that causes mobility changes, or broadband availability is an important moderator for firm digitalisation because household and firm digitalisation are complementary with respect to mobility changes. We consider that the latter issue is a different research question, which we do not aim to cover in the present analysis.

In total, mobility increased by 1.02 % over the observed time frame (see Table B.2 in the Appendix, which also provides descriptive statistics of control variables). Moreover, the increase in mobility is largely driven by a rise in short-distance travel below 30 km (see Figure B.1 in the Appendix).[18]

In a next step, we examine how the link between firm digitalisation and mobility changes evolved over the course of the pandemic. Figure 3 presents a scatter plot displaying weekly changes in mobility in each district during the observation period. The dots are coloured based on average firm digitalisation in 2020. Greener dots indicate a higher average level of digitalisation.

Mobility increases in the first weeks of 2020 in comparison to 2019 for most districts. Moreover, districts that are more digital tend to be at the centre of the distribution and no clear correlation between firm digitalisation and changes in mobility is visible. We date the start of the first Covid-19 wave to March 22$^{\mathrm{nd}}$, 2020, as this is the day the first lockdown in Germany started and many businesses, such as restaurants and coffee places, had to close in order to slow down the spread of the virus. In the last week before the start of the lockdown, a large drop in mobility can be observed. The distribution also changes and districts that are more digital tend to be located at the bottom of the distribution, where the drop in mobility is the most pronounced. With the onset of the lockdown, the distribution is altered again and digital districts are gradually shifting back towards the centre of the distribution.[19] After the first shock, mobility slowly increases, however, districts that are more digital are moving back to the bottom end of the distribution. They remain there during the second lockdown when mobility starts decreasing again for most districts. In January 2021, as the number of Covid-19 infections did not decline, the German government implemented an additional obligation for employers to offer working from home to employees if feasible. However, according to Figure 3 mobility only declines for most districts at the very beginning of this first WFH obligation. Then, we observe a slightly increasing trend until the period of the first WFH obligation ends. Nonetheless, districts that are more digital still tend to show a decrease in mobility in comparison to 2019. After the end of the first WFH obligation, districts that are more digital do not show a clear reduction in mobility anymore.

[18]Please note that the increase in overall mobility could also be due to the expansion of the 5G network, which potentially involves smaller grid cells that could imply changes in the measurement of short-distance mobility over time. In the later analysis, we control for the network quality by considering the area in a district that is not covered or not covered by all network providers.

[19]Alipour et al. (2021) observe a similar phenomenon with respect to a district's WFH potential and explain it by the strictness of confinement rules during the first lockdown that pushed people into short-time work when WFH was not possible. Hence, WFH feasibility may have played only a marginal role in reducing mobility during the first very strict lockdown.

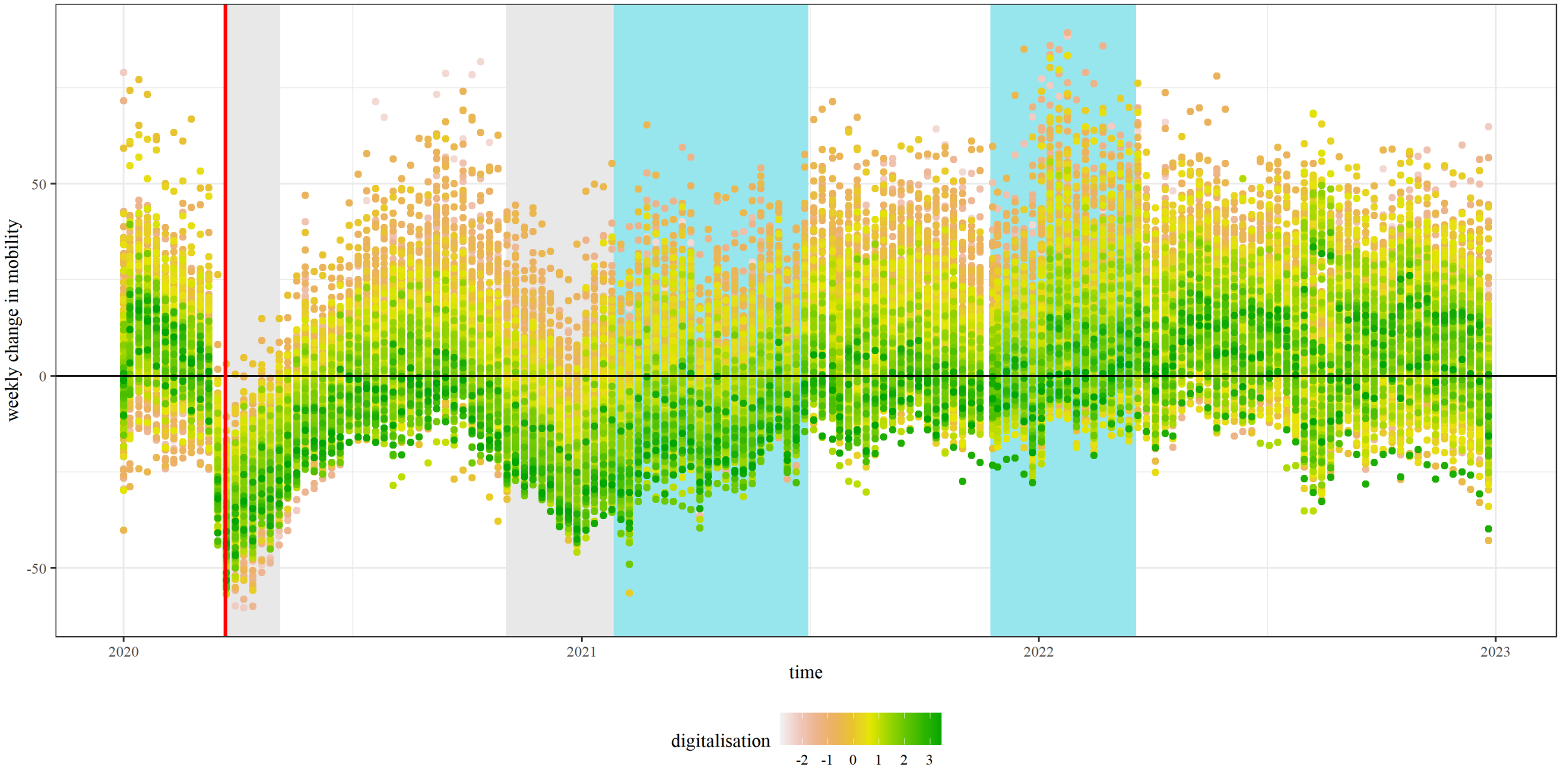

Figure 3: **Average weekly change in mobility per district over the observed time frame.** The change in mobility measures the difference between mobility on a given day and the average monthly mobility in 2019 on the same day of the week. The dots are coloured based on the average degree of firm digitalisation in a district observed in 2020. The dots are plotted on top of each other so that districts that are more digital are more visible. The red line denotes the start of the first lockdown on March 22^{nd}, 2020. White areas mark periods with no or few Covid-19 restrictions, grey areas mark lockdown periods and blue areas mark periods where the government-imposed WFH obligation was additionally in place. We observe gaps when missing data exist at the beginning of the week.

Due to high infection rates, the WFH obligation as well as stricter restrictions on contacts were re-implemented during the last quarter of 2021. As shown in the corresponding part of Figure 3, however, mobility does not drop. The correlation between mobility changes and firm digitalisation remains but it is slightly smaller than during the first WFH obligation (perhaps because people took the second WFH obligation less seriously). In spring 2022, the severity of the pandemic lessened and the second WFH obligation ended on March 20$^{\text{th}}$, 2022.[20] Also, many other Covid-19 restrictions were lifted around that date, such as restrictions on contacts for unvaccinated people. It is apparent that after the end of these restrictions, the correlation between changes in mobility and firm digitalisation continues to decline.[21]

Figure B.2 in the Appendix shows average changes in mobility for different phases of the pandemic with respect to quintiles of firm digitalisation observed in 2020 as well as in 2022 and a district's WFH potential calculated by Alipour et al. (2023) and used in Alipour et al. (2021), respectively. Average mobility changes barely differ across the corresponding quintiles of a district's WFH potential and both firm digitalisation indicators. Moreover, higher quintiles of all three indicators can unambiguously be linked to lower levels of mobility between the first open period and the end of the second WFH obligation, whereas no clear pattern is visible during the pre-pandemic phase, the first lockdown, and after the end of restrictions. Differences may exist with respect to different phases of the pandemic because firm digitalisation only represents a potential to reduce mobility that can be leveraged if needed. As the pandemic's severity as well as the strictness of restrictions fluctuated greatly over time, the mobility-reducing potential of digital technologies may have been fully realised only during specific periods of the pandemic.

5. Econometric Approach and Results

We conduct an event study based on a dynamic difference-in-differences (DiD) design with two-way fixed effects and clustered standard errors at the district level to provide inferential statistical insights into how the relationship between firm digitalisation and changes in mobility evolved. In the context of the Covid-19 pandemic, similar approaches at the regional level have been conducted by Alipour et al. (2021), Ben Yahmed et al. (2022), and Alipour et al. (2022). The

[20] This day is referred to as the German Freedom Day by many media outlets.

[21] The outlier at the bottom of the distribution during the end of the observed time frame is "Jena", which is a small district with a digital hub that is characterised by a large level of emigration. See `https://www.zeit.de/gesellschaft/grossstaedte/jena-bevoelkerungsentwicklung-zuwanderung-abwanderung` [online; accessed on 5 Jan 20023].

link between firm digitalisation and mobility changes is modelled as follows:

$$\begin{aligned}\Delta \text{mobility}_{i,t} = & \sum_{m \neq Feb\,'20} \beta^m (\text{digitalisation}_i \times \text{year-month}_m) \\ & + \sum_{m \neq Feb\,'20} \sum_{c \in C} \gamma_c^m (c_{i,t} \times \text{year-month}_m) + \text{year-month}_m + \text{district}_i + u_{i,t}.\end{aligned} \tag{1}$$

Changes in mobility relative to 2019 are observed for district i on day t. β^m represents the change in mobility in month m for a given year (measured as the difference to our reference period which is February 2020) that is related to firm digitalisation. We focus on firm digitalisation observed in January 2020, as this measure is exogenous to the onset of the Covid-19 crisis.[22] γ_c^m captures the parallel varying trend of control variable c in control variable set C for each month.[23] We include year-month fixed effects to control for common shocks that affect all districts simultaneously. Moreover, we incorporate district-level fixed effects to address potential confounding factors that result from unobserved differences between districts. In addition, observations are weighed based on their population size.

Digitalisation did significantly impact changes in mobility over the course of the pandemic as shown in Panel A of Figure 4, which displays results only with digitalisation interacted with time dummies as well as year-month and district-level fixed effects. Importantly, the β^m coefficient is close to zero and insignificant in January 2020, i.e., the month before the reference period. Thus, we do not observe a notable pre-trend.[24] After the first Covid-19 outbreak, the effect size starts to increase until it peaks in the last quarter of 2020. In October 2020, the average reduction in mobility is roughly 6.6 percentage points (pp) for every standard deviation of digitalisation. One explanation for the increase in ICT-related mobility reductions in the first months of the pandemic is that the first lockdown was very strict and many people had to stay at home

[22] A threat to endogeneity would be, for example, if more online services have emerged as a response to the onset of the crisis in districts with a greater adherence to social distancing. This could be the case because online services were more important for reaching customers in these areas.

[23] Please note that not all control variables vary over time. Moreover, we also interact the weekly incidence rate and the containment measure index with time dummies, even though they are time-varying. We do this because the sensitivity to the incidence rate as well as to Covid-19 restrictions most likely changed over time.

[24] As our pre-crisis time frame is very short, we cannot thoroughly verify whether the assumption of parallel trends, on which our event study is based, is fulfilled. To address this issue, we conduct a robustness check by re-estimating our model for the beginning of the crisis using weeks instead of months (results are presented in Figure D.3 in the Appendix and also discussed in Section 6). Also in the specification that uses weeks, we do not observe a significant pre-trend between firm digitalisation and changes in mobility. Hence, we can assume that the parallel trends assumption holds.

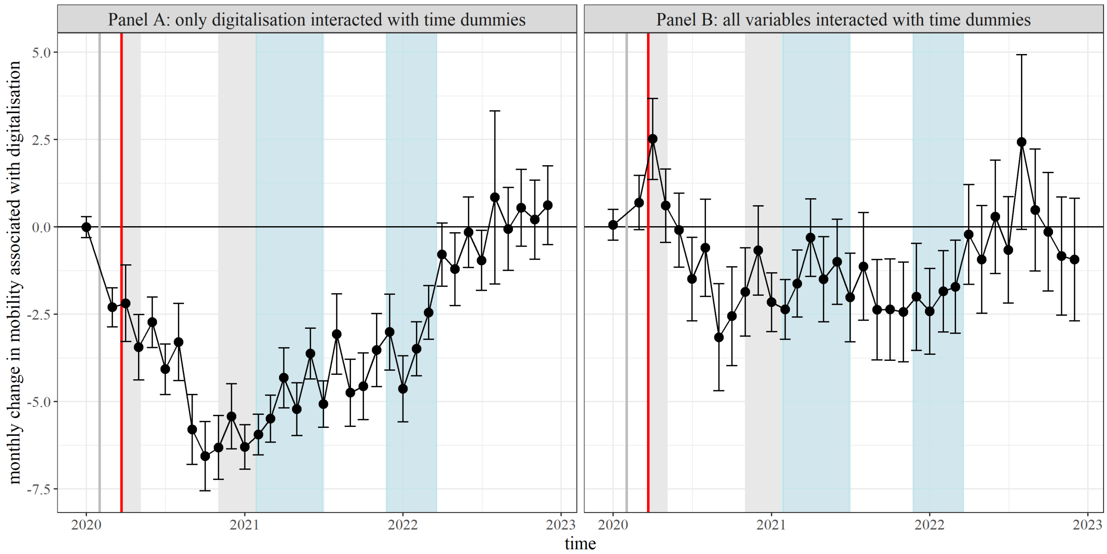

Figure 4: **Monthly change in mobility associated with digitalisation (estimated β^m coefficients).** Our reference period is February 2020 (grey line). The red line denotes the start of the first lockdown on March 22$^{\text{nd}}$, 2020. White areas mark periods with no or few Covid-19 restrictions, grey areas mark lockdown periods and blue areas mark periods where the government-imposed WFH obligation was additionally in place. Confidence intervals are at the 10% significance level.

anyway. Therefore, differences in firm digitalisation may have had a less visible impact on mobility reductions at the beginning of the crisis. In the subsequent summer months, incidence rates were low and people worked less due to the holiday season. Hence, the mobility-reducing potential of digital technologies might not have been fully exploited during this period. In autumn 2020, however, incidence rates increased again, but restrictions were less severe than during the first lockdown. In consequence, differences in firm digitalisation may have become more critical for changes in mobility. Moreover, the effect size may also have increased during the initial months, as digital capacities that allow for social distancing had to be built, such as online sales channels as well as VPN and fast internet connections (e.g., Barrero et al., 2021; Bloom et al., 2021). We assume that firms which already had a certain digital proficiency prior to the crisis had advantages in this regard (cf. Cariolle and Léon, 2022).

In 2021, the effect size slightly decreases and levels off at around roughly -4 pp until the end of the year. Moreover, during the second WFH obligation, the effect size further declines. After lifting most restrictions in March 2022, the effect size continues to diminish and becomes insignificant for most months.

When we allow for differential time trends of control variables (displayed in Panel B of Figure

4), digitalisation coefficients still tend to be negative and significant for most months of the first two years of the pandemic, however, the effect size is notably smaller. Surprisingly, we find a significantly positive effect in April 2020 (the middle of the first lockdown period). Alipour et al. (2021) observe a very similar phenomenon when analysing the link between a district's WFH potential and changes in mobility at the beginning of the crisis and controlling for covariates. The authors explain the positive link by the strictness of the first lockdown, in which many employees were put on short-time work and many (rather non-digital) establishments had to close in order to avoid contagion. This reasoning is confirmed by Ben Yahmed et al. (2022), who show that regions with lower digital capital had higher short-time work usage rates at the beginning of the crisis. Thus, during this time, the widespread use of short-time work and closed factories might have reduced mobility especially in low-digitalised regions. This situation at the beginning of the pandemic attenuates the association between a district's mobility reductions and its digitalisation level and can even lead to a positive coefficient. In fact, the sign of our focal coefficient is only reversed, if we include time-varying effects of socio-economic and demographic characteristics that might partially capture the effect of a district's feasibility to work from home on mobility (see Table 1, discussed in the next paragraph).

In Panel B, we observe the maximum realised mobility reduction in September 2020, in which the differential decrease is 3.2 pp for every standard deviation of digitalisation. Moreover, after the end of the second WFH obligation, the effect size declines and becomes insignificant. Hence, we also find diminishing effects after the end of restrictions when we condition on differential time trends of control variables. Thus, we do not find evidence for long-lasting environmental improvements.

In a next step, we re-estimate Equation (1) but summarise differential time trends by the different phases of the pandemic. Table 1 shows that the digitalisation coefficient for the post-pandemic phase is always insignificant, independent of the considered control variables. Furthermore, the coefficient of the post-pandemic phase is always less negative than the coefficients of previous phases in which digitalisation can be unambiguously linked to a decrease in mobility. The difference to these previous phases is predominantly significant at the 10% threshold. Thus, this specification also strongly indicates that the effect size diminishes in the post-pandemic phase.

In the last step, we estimate the average change in mobility that can be linked to firm digitalisation during the two years of the pandemic (from March 22$^{\text{nd}}$, 2020 to March 19$^{\text{th}}$, 2022), considering all covariates. Column (1) of Table C.3 in the Appendix displays a negative and sig-

Table 1: DiD results providing insights into changes in the link between mobility reductions and firm digitalisation for different phases of the pandemic.

	dependent variable: Δ mobility						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
digitalisation (Jan '20)							
× (1) 1st lockdown	-2.079***	-2.050***	1.096^{+}	-0.340	1.289^{+}	-0.315	1.732**
	(-3.68)	(-3.87)	(1.79)	(-0.50)	(1.89)	(-0.51)	(2.76)
× (2) 1st open period	-3.920***	-3.902***	-2.479***	-2.776***	-1.851**	-2.843***	-1.504*
	(-8.70)	(-8.97)	(-3.58)	(-4.50)	(-2.80)	(-5.35)	(-2.17)
× (3) 2nd lockdown/ 1st WFH o.	-4.895***	-5.142***	-2.914***	-2.817***	-2.214***	-3.328***	-1.728**
	(-13.72)	(-14.17)	(-5.20)	(-5.30)	(-4.14)	(-8.10)	(-3.05)
× (4) 2nd open period	-3.837***	-4.046***	-3.177***	-3.056***	-3.319***	-3.408***	-2.237**
	(-7.34)	(-7.72)	(-3.82)	(-4.02)	(-4.17)	(-5.73)	(-2.69)
× (5) 2nd WFH obligation	-3.028***	-3.296***	-2.352***	-1.738*	-3.487***	-3.186***	-2.207**
	(-6.83)	(-7.66)	(-3.44)	(-2.54)	(-4.92)	(-5.67)	(-3.19)
× (6) post-pandemic	0.242	-0.0244	0.502	0.612	-1.542	-0.276	-0.291
	(0.40)	(-0.04)	(0.55)	(0.63)	(-1.57)	(-0.35)	(-0.30)
year-month fixed effects	x	x	x	x	x	x	x
district-level fixed effects	x	x	x	x	x	x	x
pandemic controls		x					x
socioeconomic controls			x				x
infrastructure controls				x			x
demographic controls					x		x
geographic controls						x	x
observations	433999	433999	433999	433999	433999	433999	433999
R^2	0.57	0.58	0.58	0.57	0.59	0.58	0.62
$\beta^1 = \beta^6$	0.00	0.00	0.52	0.34	0.00	0.96	0.03
$\beta^2 = \beta^6$	0.00	0.00	0.00	0.00	0.67	0.00	0.08
$\beta^3 = \beta^6$	0.00	0.00	0.00	0.00	0.32	0.00	0.02
$\beta^4 = \beta^6$	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\beta^5 = \beta^6$	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: β^m coefficients of Equation (1) estimated using OLS. t statistics in parentheses. Clustered standard errors. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Observations are weighted based on their population size. The time frame is split into different phases as presented in Figure 3. The pre-Covid-19 phase is used as a reference period. Fixed effects for every phase are additionally included. The table also includes t-tests for the equality of coefficients. (1) no control variables; (2) only controlled for the pandemic situation; (3) only controlled for socioeconomic characteristics; (4) only controlled for characteristics that relate to a district's infrastructure; (5) only controlled for demographic characteristics; (6) only controlled for geographic characteristics; (7) all control variables included.

nificant digitalisation coefficient, indicating that firm digitalisation can on average be associated with mobility reductions during the crisis. The effect size is -1.68 pp. Column (2) and Column (3) show results for daytime and nighttime mobility separately. We also find a significantly negative link between firm digitalisation and daytime mobility changes, but the effect size is much smaller and insignificant for nighttime mobility, which is highly plausible as most people only work and engage in commercial activities during daytime. Column (4) presents findings only for working days and Column (5) only for weekends estimated with daytime mobility changes. We find that the coefficient is slightly smaller at weekends, which is plausible as people usually do not work during these days, but commercial activities may continue. Another reason for a decrease in mobility associated with digitalisation on weekends could be that people spread their working hours over the entire week when working from home and also work at weekends (e.g., McDermott and Hansen, 2021).

6. Robustness

Our event study relies on the assumption that no difference in mobility changes with respect to firm digitalisation between districts would have occurred if the Covid-19 outbreak did not happen. To explore this issue, we re-estimate Equation (1) for the period between January 7th, 2020 and May 4th, 2020, but analyse weekly instead of monthly differences. We use the week before Shrove Monday 2020 as a reference period because the first large-scale Covid-19 outbreaks occurred in Germany as part of the carnival festivities in 2020. Figure D.3 in the Appendix shows that no statistically significant difference in mobility changes with respect to firm digitalisation exists for the weeks before the first large-scale outbreaks.

As firms heavily invested in digital infrastructure in the course of the pandemic, one reason for insignificant effects in the post-pandemic phase could be that firm digitalisation changed to such an extent in the observed time frame that we do not find an effect in 2022 if we consider firm digitalisation observed in 2020. To explore this issue, we conduct the same event study but with firm digitalisation measured in 2022. Figure D.4 and Table D.4 in the Appendix show that changes in the degree of firm digitalisation during the pandemic do not appear to cause the diminishing effect size, as the results are generally very similar to our main results.

As stated above, one drawback of our web-based digitalisation indicator is that we only observe the degree of digitalisation for firms that have a website. To address this issue, we modify the way we average the degree of firm digitalisation at the district level. To this end, we assume that there are $J + K = N$ firms in a district i. Firm $j \in J$ has a website and firm $k \in K$ does not. We conjecture that firms without a website address available in the MUP do not have a website, i.e., they are part of set K. Moreover, we suppose that these firms have a lower degree of digitalisation than firms with a website and set their digitalisation score to zero. Since firm digitalisation of firms in set K is zero, we divide the sum of our web-based predictions by the total number of firms in a district to adjust our indicator for firms without a website (see Equation [2]):

$$\text{digitalisation}_i = \frac{\sum_{j_i \in J_i} \text{digitalisation}_{j_i} + \sum_{k_i \in K_i} \text{digitalisation}_{k_i}}{N_i} = \frac{\sum_{j_i \in J_i} \text{digitalisation}_{j_i}}{N_i}. \tag{2}$$

Column (1) and Column (2) of Table D.5 in the Appendix show results with respect to different phases of the pandemic, including all control variables for modified firm digitalisation observed in 2020 and in 2022, respectively. The coefficients of both modified digitalisation indicators point in the same direction as in the estimation with unmodified firm digitalisation. For the indicator observed in 2020, we find mostly insignificant effects. For 2022, however, we observe weakly significant results until the end of the second open period and no significant effect in the post-pandemic period.

Despite the fact that the scraping algorithm has changed between both scraping periods and the size of predictions at the firm level is not reliably comparable between both scraping periods, we also provide insights about the extent to which results differ if we consider the change in predictions instead of the level of firm digitalisation. To this end, we calculate the standardised difference between modified firm digitalisation observed in 2020 and in 2022. This allows us to consider changes in the degree of digitalisation for firms that have a website as well as to take the increase in the number of firms with a website into account. Column (3) in Table D.5 displays that coefficients point into familiar directions when considering changes in firm digitalisation at the district level, but only the coefficient for the first open period shows a weakly significant negative effect.

Column (4) of Table D.5 shows coefficients of household broadband availability as a proxy for the level of household digitalisation. Firm digitalisation is excluded from the estimation. In this specification, coefficients are predominately insignificant, indicating that household broadband availability is not as relevant for changes in mobility as firm digitalisation. Column (5) and

Column (6) show results of unmodified firm digitalisation in 2020 and in 2022 but with districts not weighted by their population size. Digitalisation coefficients are comparable to our main results.

Moreover, in our main analysis, we conjecture that firm digitalisation leads to a decrease in mobility via remote work and e-commerce. To provide some evidence in favour of this mechanism, we analyse whether our web-based digitalisation indicator can indeed be associated with increased firm-level remote work and e-commerce at the onset of the crisis. For this purpose, we use the Mannheim Innovation Panel (MIP) in 2021, in which German firms were asked about the percentage of employees that worked from home before the pandemic as well as during the first and second lockdown and whether they increased e-commerce activities at the beginning of the crisis (Rammer et al., 2021). Merging the MIP 2021 with the MUP allows us to analyse this information for 3014 firms. Results with respect to remote work are displayed in Table D.6 in the Appendix. We find that the share of employees that work from home increased by 6 to 7 pp if firm digitalisation observed in 2020 is one standard deviation larger. Results with respect to e-commerce are provided in Table D.7 in the Appendix. We also observe that firms which are more digital are more likely to have expanded digital products, services, and sales channels with the onset of the crisis.

Furthermore, we analyse how firm digitalisation relates to the link between a district's WFH potential and mobility reductions. In Table D.8 in the Appendix, we replace firm digitalisation by a district's capacity to work from home according to Alipour et al. (2023).[25] Our results indicate that mobility reductions at daytime are also related to a district's WFH potential. However, the link becomes insignificant when we additionally include firm digitalisation, whereas the latter remains significant. This finding suggests that firm digitalisation better explains variation in changes in mobility than a district's WFH potential, which either could be because firm digitalisation is the more precisely measured variable or because firm digitalisation has further impact channels such as e-commerce.[26]

[25]For a description of the variable, see Appendix A.1.

[26]Also, we looked into the robustness of results with respect to spatial correlation and estimated a spatial Durbin regression model, including spatial lags of our dependent variable and independent variables. Our results are robust in the sense that we find a diminishing effect in the post-pandemic period and no significant effect of spatially lagged firm digitalisation. Results can be retrieved from the authors upon request.

7. Discussion & Conclusion

Given the climate crisis and sharply rising energy costs, discussions on the exploitation of the mobility-reducing potential of digital technologies are repeatedly part of the public debate. Due to the strong need to avoid physical contact, it is generally believed that the Covid-19 pandemic has accelerated the utilisation of this potential. We contribute to the discussion by quantifying the actual extent to which firm digitalisation can be linked to mobility reductions from January 2020 to December 2022. Using German data at the district level and considering a broad variety of control variables, we find that mobility decreased on average by 1.68 pp in comparison to 2019 for every standard deviation of firm digitalisation during the first two years of the pandemic. We observe the largest mobility reductions associated with digital technologies in the last quarter of 2020. During this period mobility decreased up to 3.2 pp for every standard deviation of firm digitalisation if we control for differential trends of covariates and up to 6.6 pp if we do not. Moreover, we observe that the effect size diminishes and becomes insignificant after most Covid-19 restrictions were lifted in March 2022, suggesting no long-lasting environmental improvements.

This result raises the question of why ICT-enabled mobility reductions declined after the end of most restrictions. In Section 2, we hypothesise that even though factors that promote telecommunications-transportation substitution improved during the pandemic, mobility reductions can diminish for several reasons, which we now discuss individually. A mentioned reason that explains why mobility increased again, is that managers still prefer employees to work on-site as it facilitates supervision and interaction. However, we consider this reason rather unlikely as questionnaire-based surveys confirm that a large share of employees still work remotely. The same applies to the argument that, after the pandemic, people take long-distance trips more often. We do not consider this to be a significant reason because after the pandemic long-distance travel is roughly at the same level as during the second open period, in which digitalisation can still be linked to mobility reductions (see Figure B.1 in the Appendix). An additional argument is that people move further away from their working place where rents are cheaper because they have to commute less frequently. However, if people would move to another district a notable positive correlation between firm digitalisation and changes in in-commuters should exist. In fact, we find a slightly negative correlation of -0.04 if we do not weigh by population size and only a small positive correlation of 0.08 if we do. Another argument why this reason is not substantial is that if people move away, ICT-enabled mobility reductions should decline gradually, but both, the descriptive and the econometric analysis, strongly suggest that the relationship changed at a certain point in time, namely when most restrictions were lifted. Figure B.1 in the Appendix also reveals that short-distance travel increased to a greater extent than long-distance travel. Hence, it could also be that an expansion of the 5G network caused an overall increase in mobility, as smaller grid cells allow us to observe short-distance mobility at a more granular level. However, this issue only affects the link between digitalisation and changes in mobility if the 5G expansion correlates with our measure of firm digitalisation. If this is the case, ICT-enabled mobility reductions should also tend to gradually decline, but, as stated above, the relationship changes rather abruptly.

The compensation of social and self-realisation needs during leisure time as well as a preference for hybrid shopping remain as possible reasons for diminishing ICT-enabled mobility reductions, which both point to Salomon's (1986) argument that people have an intrinsic need for mobility that prevents them from comprehensive telecommunications-transportation substitution. Since this is likely to be the case, we conclude that it is more desirable from a societal perspective to promote green, carbon neutral mobility patterns, than advocating the replacement of physical travel by digital solutions.

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Appendix A. Variable description

Table A.1: **Description of variables.**

variable	description	source
Main variables		
mobility	The change in switches between phone cells per mobile device at a given day relative to monthly pre-crisis averages in 2019 for the same weekday (in %, 01/01/'20 - 31/12/'22) at the district level. The change in mobility is reported for daytime and nighttime separately (daytime mobility: 6 a.m. to 10 p.m.; nighttime mobility: 10 p.m. to 6 p.m.). Overall mobility is a weighted mean of daytime and nighttime mobility. Mobility data is being processed and provided by the Teralytics AG. Please note that we observe missing values over the entire time period.	Destatis (2023*c*). Mobile Network Data. (`https://www.destatis.de/EN/Service/EXDAT/Datensaetze/mobility-indicators-mobilephone.htm` [retrieved on 03/01/2023]). Data was obtained upon request.
digitalisation	We train a Random Forest regression model on a large German newspaper corpus. The fitted model allows for predicting the likelihood that a firm's website content relates to digitalisation. These predictions are used as a continuous indicator for firm digitalisation. For this purpose, we scraped 750,000 firm websites in January 2020 and 1,300,000 firm websites in December 2022. For more details see Axenbeck and Breithaupt (2022). Validity checks with external data show a clear relationship with already established digitalisation indicators at the firm, sectoral, and regional level. We average predictions at the district level.	Web addresses are retrieved from the Mannheim Enterprise Panel (MUP), which comprises a large set of German firms (Bersch et al., 2014). The MUP is fed by data from Creditreform.

Table A.1: **Description of variables.**

variable	description	source
Control variables		
Pandemic characteristics		
weekly cases	Sum of confirmed Covid-19 cases in the last 7 days per 100,000 inhabitants (01/03/'20 - 31/12/'22) at the district level considered as a rolling window. We include weekly cases and not daily cases as a control variable, because weekly cases better reflect the number of people that are infectious and it is also the number, which was mostly communicated in the media. We, therefore, assume that people made their mobility decisions on weekly cases. We set values before 01/03/'20 to zero.	Destatis (2023*a*) (`https://www.corona-daten-deutschland.de/dataset/infektionen_kreise` [retrieved on 04/01/2021]).
containment measures	Index that captures the severity of containment measures at the district level (01/03/'20 - 30/11/'22). The index was calculated by infas 360. We set values that are before the observed time frame to zero. We use the last observed value to replace missing values after the observed time frame.	Destatis (2023*a*) (`https://www.corona-daten-deutschland.de/dataset/massnahmenindex_kreise_pro_tag` [retrieved on 04/01/2023]).
socioeconomic characteristics		
share of academics	Number of persons aged 15 or older with a Bachelors, Masters, Ph.D. or comparable university degree divided by the number of inhabitants being 15 or older in 2019 at the district level.	Destatis (2023*a*) (number of academics, `https://www.corona-daten-deutschland.de/dataset/bildungsniveau` [retrieved on 02/06/2022], number of inhabitants: `https://www.corona-daten-deutschland.de/dataset/bevoelkerung` [retrieved on 02/06/2022]).
GDP per inhabitant	Gross domestic product in €1,000 per person in 2020 at the district level.	Destatis (2023*a*) (`https://www.corona-daten-deutschland.de/dataset/volkswirtschaftliche_gesamtrechnung` [retrieved on 2/06/2022]).

Table A.1: **Description of variables.**

variable	description	source
low-income households	The number of low-income households (≤ €1,000 per month) in 2019 at the district level per 1,000 inhabitants.	Destatis (2023*a*) (number of low-income households: `https://www.corona-daten-deutschland.de/dataset/private_finanzen` [retrieved on 12/11/2022], number of inhabitants: `https://www.corona-daten-deutschland.de/dataset/bevoelkerung` [retrieved on 02/06/2022]).
people on social benefits	The number of recipients of benefits under SGB II and the number of recipients of benefits under SGB XII per 1,000 inhabitants in 2017.	Destatis (2023*a*) (`https://www.corona-daten-deutschland.de/dataset/sozialindikatoren` [retrieved on 12/11/2022]).
share of workers in the service sector	The number of people that work in the service sector divided by all workers observed at the end of 2019.	Destatis (2023*a*) (`https://www.corona-daten-deutschland.de/dataset/arbeitsmarktstruktur` [retrieved on 12/11/2022]).
infrastructure		
cars per person	Number of cars per 1,000 inhabitants in 2021.	Destatis (2023*a*) (`https://www.corona-daten-deutschland.de/dataset/verkehr` [retrieved on 12/11/2022]).
≥ 50 Mbit/s	Share of households with a broadband availability of at least 50 Mbit/s in each district in 2020.	atene KOM GmbH (2021). Breitbandatlas des Bundes (German Broadband Atlas) - Release 2/2021. Data is restricted in usage. Access can be requested at atene KOM GmbH (`https://atenekom.eu/project/breitbandatlas/` [retrieved on 09/04/2021]).
not covered by all	Area that is not covered by 4G, 5G or 5G DSS by every network provider in % for the year 2022. Please note that information is only available for 388 districts. Missing vs are set to zero and an additional dummy variable is added that controls whether the information is available or not.	Bundesnetzagentur (2022). Mobilfunkmonitoring (`https://www.breitband-monitor.de/mobilfunkmonitoring/download` [retrieved on 22/12/2022]).

Table A.1: **Description of variables.**

variable	description	source
not covered	Area that is not covered by 4G, 5G or 5G DSS by any network provider in % for the year 2022. Please note that information is only available for 388 districts. Missing values are set to zero and an additional dummy variable is added that controls whether the information is available or not.	Bundesnetzagentur (2022). Mobilfunkmonitoring (`https://www.breitband-monitor.de/mobilfunkmonitoring/download` [retrieved on 22/12/2022]).
demographic characteristics		
share of men	The number of male inhabitants divided by all inhabitants in 2020.	Destatis (2023*a*) (number of male inhabitants & number of inhabitants, `https://www.corona-daten-deutschland.de/dataset/bevoelkerung` [retrieved on 02/06/2022]).
not of working age	The percentage of the population in a district that is either under 15 years old or over 65 years old.	Destatis (2023*a*) (number of people younger than 15 years or older than 65 years & number of inhabitants, `https://www.corona-daten-deutschland.de/dataset/bevoelkerung` [retrieved on 02/06/2022]).
number of inhabitants	The number of people that are registered in a district (divided by 1,000).	Destatis (2023*a*) (`https://www.corona-daten-deutschland.de/dataset/bevoelkerung` [retrieved on 02/06/2022]).
changes in population	Changes in % of the number of people that are registered in a district. We consider changes in the population between 2019 and 2020 for the year 2020 and changes between 2019 and 2021 for the years 2021 and 2022 (as information for 2022 was not available when the analysis was conducted).	GENESIS-ONLINE: Table 12411-0015 (`https://www-genesis.destatis.de/genesis/online` [retrieved on 02/06/2022]).
population density	Inhabitants per square kilometre in 2019 at the district level.	Destatis (2023*a*) (`https://www.corona-daten-deutschland.de/dataset/besiedlung` [retrieved on 2/06/2022]).
in-commuters	Changes in the number of employees that work in a district but live elsewhere in %. We consider changes in in-commuters between 2019 and 2020 for the year 2020 and changes between 2019 and 2021 for the years 2021 and 2022 (as information for 2022 was not available when the analysis was conducted).	Bundesagentur für Arbeit (2022). Pendlerverflechtungen der sozialversicherungspflichtig Beschäftigten nach Kreisen - Deutschland (`https://statistik.arbeitsagentur.de` [retrieved on 01/12/2022]).

Table A.1: **Description of variables.**

variable	description	source
out-commuter	Changes in the number of employees that live in a district but work elsewhere in %. We consider changes in out-commuters between 2019 and 2020 for the year 2020 and changes between 2019 and 2021 for the years 2021 and 2022 (as information for 2022 was not available when the analysis was conducted).	Bundesagentur für Arbeit (2022). Pendlerverflechtungen der sozialversicherungspflichtig Beschäftigten nach Kreisen - Deutschland (`https://statistik.arbeitsagentur.de` [retrieved on 01/12/2022]).
one-person households	Number of people per 1,000 inhabitants that live in a one-person household in a district for the year 2019.	Destatis (2023*a*) (number of one-person households: `https://www.corona-daten-deutschland.de/dataset/haushalte` [retrieved on 01/11/2022], number of inhabitants: `https://www.corona-daten-deutschland.de/dataset/bevoelkerung` [retrieved on 02/06/2022]).
living space per household	Average living space per household in a district for the year 2019.	Destatis (2023*a*) (`https://www.corona-daten-deutschland.de/dataset/wohnsituation` [retrieved on 01/11/2022]).

Table A.1: **Description of variables.**

variable	description	source
geographic characteristics		
city	A dummy variable that is one if a district is a "Stadtkreis" or a "Kreisfreie Stadt" (city) and zero if a district is a "Landkreis" or "Kreis" (countryside area).	atene KOM GmbH (2021). Breitbandatlas des Bundes (German Broadband Atlas) - Release 2/2021. Data is restricted in usage. Access can be requested at atene KOM GmbH (`https://atenekom.eu/project/breitbandatlas/` [retrieved on 09/04/2021]).
West Germany	A dummy that is one if a district is in the former Federal Republic of Germany (West Germany) and that is zero if a district is in the former German Democratic Republic (East Germany).	Destatis (2023*a*) (`https://www.corona-daten-deutschland.de/dataset/raumordnung` [retrieved on 01/11/2022]).
other variables		
WFH potential	The percentage of employees who can potentially work from home according to their self-assessment and considered at the location of their workplace. The calculation is described in detail in Alipour et al. (2023).	Destatis (2023*a*) (`https://www.corona-daten-deutschland.de/dataset/arbeitsmarktstruktur` [retrieved on 01/11/2022]).
number of firms	Number of firms in a district in March 2020.	Destatis (2023*a*) (`https://www.corona-daten-deutschland.de/dataset/firmeninformationen` [retrieved on 05/1/2023]).

Appendix B. Additional Descriptive Statistics

Table B.2: Overview of descriptive statistics.

	N	mean	sd	p10	p90
Δ mobility	433999 (daily)	1.02	17.87	-21.33	22.67
Δ mobility daytime	433999 (daily)	5.04	18.24	-17.00	27.00
Δ mobility nighttime	433999 (daily)	-7.02	21.69	-34.00	18.00
digitalisation (Jan ’20)	400	0.00	1.00	-1.16	1.33
digitalisation (Dec ’22)	400	0.00	1.00	-1.22	1.33
digitalisation modified (Jan ’20)	400	0.00	1.00	-1.35	1.39
digitalisation modified (Dec ’22)	400	0.00	1.00	-1.19	1.34
Δ digitalisation modified (Dec ’22)	400	0.00	1.00	-1.12	1.35
weekly cases	433999 (daily)	289.68	464.14	0.80	852.60
containment measures	433999 (daily)	31.58	20.03	8.01	58.76
share of academics	400	0.16	0.05	0.11	0.22
GDP per inhabitant in €1000	400	37.08	16.05	24.80	53.80
low-income households per 1,000 inhabitants	400	69.71	43.48	23.26	133.49
people on social benefits per 1,000 inhabitants	400	8.99	4.14	4.20	15.20
share of workers in the service sector	400	0.49	0.07	0.41	0.58
cars per 1,000 person	400	549.82	77.11	434.00	630.00
$\geq$ 50 mbit/s	400	91.94	7.23	81.50	98.80
not covered by all	400	15.22	10.21	1.39	29.21
not covered	400	2.45	3.16	0.00	6.55
share of men	400	0.49	0.01	0.49	0.50
share not of working age	400	0.36	0.03	0.33	0.40
number of inhabitants divided by 1,000	400	207.77	244.81	72.04	346.97
change in population	800 (’19-’20, ’19 -21)	0.00	0.00	-0.01	0.01
population density per square kilometre	400	536.46	709.62	83.00	1484.00
change in out-commuters	800 (’19-’20, ’19 -21)	0.02	0.02	-0.01	0.05
change in in-commuters	800 (’19-’20, ’19 -21)	0.02	0.03	-0.02	0.06
one-person households per 1,000 inhabitants	400	198.38	59.32	135.33	292.64
living space per household	400	115.32	18.40	89.00	138.00
city	400	0.26	0.44	0.00	1.00
West Germany	400	0.81	0.39	0.00	1.00

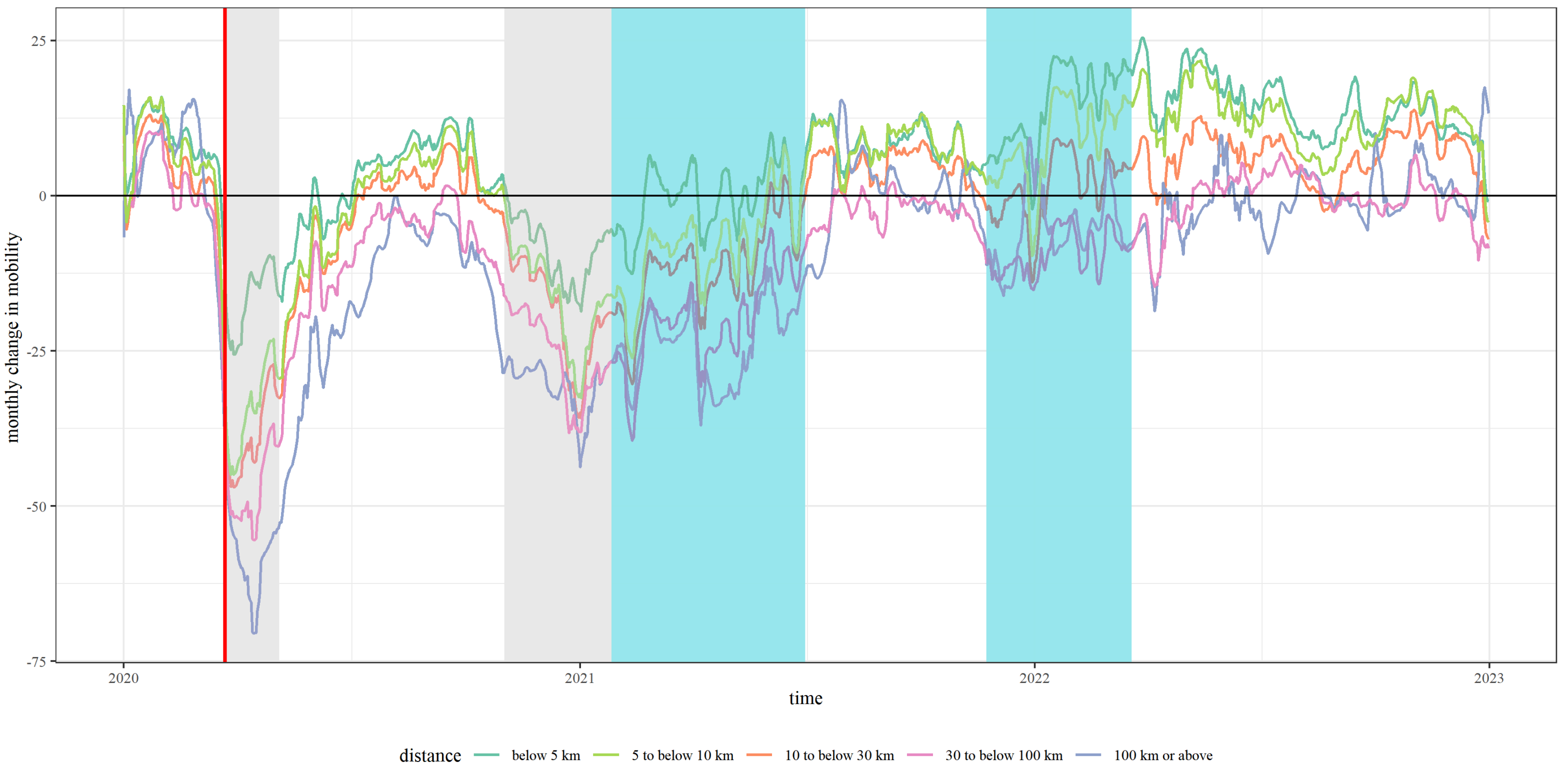

Figure B.1: **Change in mobility compared to 2019 by distance in % (7-day average).** The red line denotes the start of the pandemic on March 22^{nd}, 2020. Grey areas mark lockdown periods and blue areas mark periods where a government-imposed WFH obligation was additionally in place. Data Source: Destatis (2023*b*).

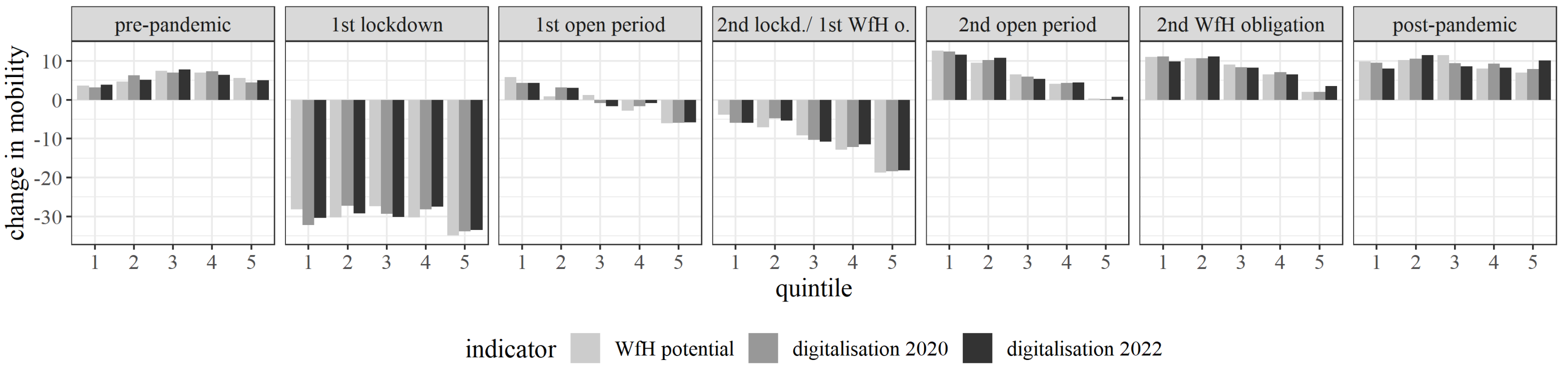

Figure B.2: **Comparison between quintiles of the WFH potential derived by Alipour et al. (2023) and the web-based digitalisation indicator with respect to differences in average mobility.**

Appendix C. Results With Respect to the Average Effect

To measure the average effect during the two years of the pandemic (from March 22$^{\text{nd}}$, 2020 to March 19$^{\text{th}}$, 2022), we estimate the following linear model using year-month fixed effects and clustered standard errors at the district level:

$$\Delta \text{mobility}_{i,t}^{h} = \alpha + \beta \, \text{digitalisation}_i + \sum_{c \in C} \gamma_c c_{i,t} + u_{i,t}. \tag{C.1}$$

h refers to the period (daytime, nighttime or the entire day) for which mobility is observed in district i at day t. C denotes our set of control variables. Observations are weighted based on their population size.

Table C.3: Average decrease in mobility associated with digitalisation considering mobility changes over the entire day, daytime mobility changes, nighttime mobility changes as well as differences between working days and weekends during the two pandemic years. Firm digitalisation is observed in 2020.

	dependent variable: Δ mobility				
	(1)	(2)	(3)	(4)	(5)
digitalisation (Jan '20)	-1.681***	-2.374***	-0.297	-2.565***	-1.900***
	(-3.44)	(-4.60)	(-0.59)	(-5.01)	(-3.50)
year-month fixed effects	x	x	x	x	x
pandemic controls	x	x	x	x	x
socioeconomic controls	x	x	x	x	x
infrastructure controls	x	x	x	x	x
demographic controls	x	x	x	x	x
geographic controls	x	x	x	x	x
observations	288399	288399	288399	205599	82800
R^2	0.566	0.532	0.474	0.565	0.501

Notes: Equation C.1 estimated using OLS and all control variables. t statistics in parentheses. Clustered standard errors. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Observations are weighted based on their population size. (1) mobility changes over the entire day; (2) mobility changes during daytime; (3) mobility changes during nighttime; (4) mobility changes on working days during daytime; (5) mobility changes on weekends during daytime.

Appendix D. Results of Robustness Checks

Appendix D.1. Parallel Trends

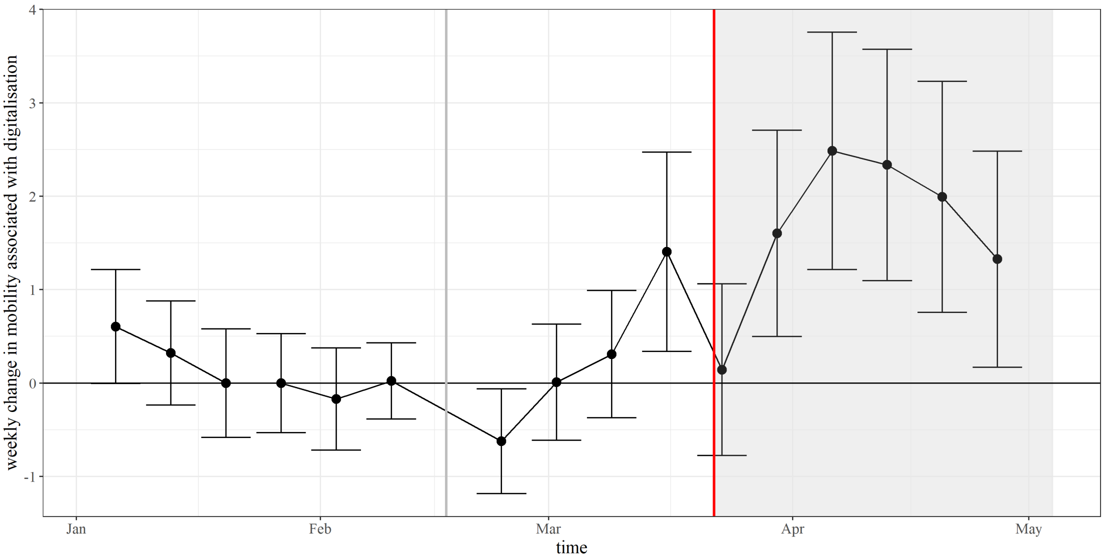

Figure D.3: **Analysis of parallel trends before the Covid-19 pandemic (estimated β^m coefficients).** Equation (1) is estimated at the weekly level. Digitalisation and control variables are interacted with time dummies. We estimate the time frame between January 7th, 2020, and May 4th, 2020. The latter date denotes the end of the first lockdown. We exclude the first week in January because it is a holiday period with irregular mobility patterns. We use the week before Shrove Monday 2020 as the reference period, as the first large-scale Covid-19 outbreaks occurred in Germany as part of carnival festivities (grey line). Digitalisation is observed in 2020. Confidence intervals are at the 10% significance level.

Appendix D.2. Digitalisation Observed in December 2022

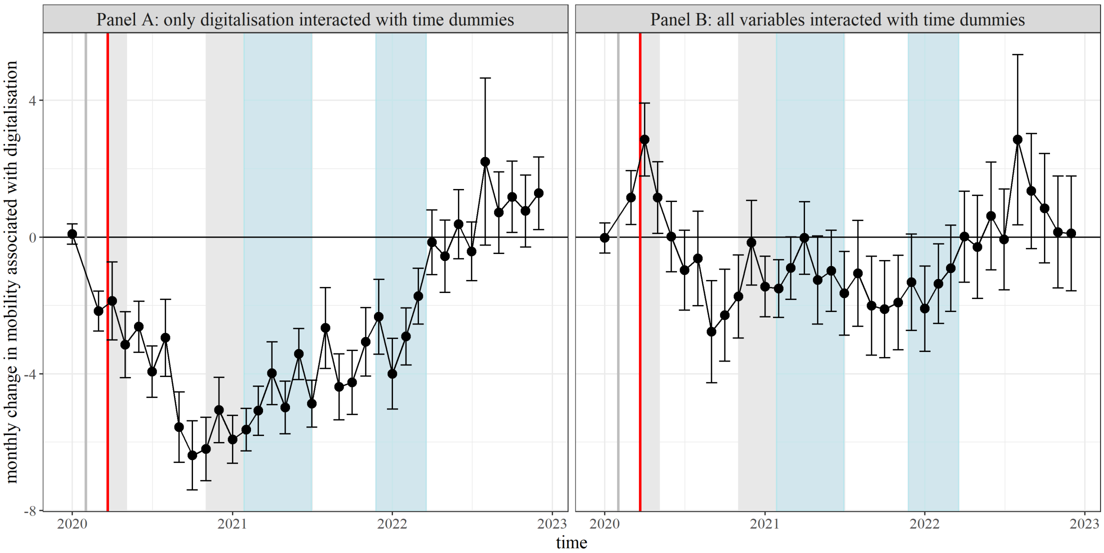

Figure D.4: **Monthly change in mobility associated with digitalisation observed in December 2022 (estimated β^m coefficients).** Our reference period is February 2020 (grey line). The red line denotes the start of the first lockdown on March 22nd, 2020. White areas mark periods with no or few Covid-19 restrictions, grey areas mark lockdown periods and blue areas mark periods where the government-imposed WFH obligation was additionally in place. Confidence intervals are at the 10% significance level.

Table D.4: DiD results providing insights into changes in the link between mobility reductions and firm digitalisation with respect to different phases of the pandemic using digitalisation observed in 2022.

	dependent variable: Δ mobility						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
digitalisation (Dec '22)							
× (1) 1st lockdown	-1.816**	-1.900***	1.439*	0.254	2.069**	0.411	2.168***
	(-3.10)	(-3.53)	(2.31)	(0.39)	(3.20)	(0.62)	(3.83)
× (2) 1st open period	-3.769***	-3.777***	-2.352***	-2.303***	-1.531*	-2.431***	-1.250^{+}
	(-8.15)	(-8.54)	(-3.38)	(-3.92)	(-2.33)	(-4.20)	(-1.90)
× (3) 2nd lockdown/ 1st WFH o.	-4.654***	-4.959***	-2.529***	-2.287***	-1.709**	-2.761***	-1.306*
	(-13.07)	(-13.88)	(-4.72)	(-4.51)	(-3.22)	(-6.16)	(-2.41)
× (4) 2nd open period	-3.561***	-3.813***	-2.811***	-2.358**	-2.758***	-2.897***	-2.004*
	(-7.02)	(-7.57)	(-3.47)	(-3.28)	(-3.55)	(-4.62)	(-2.50)
× (5) 2nd WFH obligation	-2.436***	-2.748***	-1.492*	-0.496	-2.236**	-2.466***	-1.735**
	(-5.25)	(-6.20)	(-2.27)	(-0.76)	(-3.25)	(-4.29)	(-2.60)
× (6) post-pandemic	0.893	0.591	1.384	1.929*	-0.0779	0.618	0.359
	(1.50)	(1.00)	(1.52)	(2.18)	(-0.09)	(0.80)	(0.39)
year-month fixed effects	x	x	x	x	x	x	x
district-level fixed effects	x	x	x	x	x	x	x
pandemic controls		x					x
socioeconomic controls			x				x
infrastructure controls				x			x
demographic controls					x		x
geographic controls						x	x
observations	433999	433999	433999	433999	433999	433999	433999
R^2	0.57	0.59	0.58	0.58	0.59	0.58	0.62
$\beta^1 = \beta^6$	0.00	0.00	0.95	0.07	0.02	0.81	0.04
$\beta^2 = \beta^6$	0.00	0.00	0.00	0.00	0.03	0.00	0.02
$\beta^3 = \beta^6$	0.00	0.00	0.00	0.00	0.01	0.00	0.01
$\beta^4 = \beta^6$	0.00	0.00	0.00	0.00	0.00	0.00	0.00
$\beta^5 = \beta^6$	0.00	0.00	0.00	0.00	0.00	0.00	0.00

Notes: Equation 1 estimated using OLS. t statistics in parentheses. Clustered standard errors. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Observations are weighted based on their population size. The time frame is split into different phases as presented in Figure 3. The pre-Covid-19 phase is used as a reference period. Fixed effects for every phase are additionally included. The table also includes t-tests for the equality of coefficients. (1) no control variables; (2) only controlled for the pandemic situation; (3) only controlled for socioeconomic characteristics; (4) only controlled for characteristics that relate to a district's infrastructure; (5) only controlled for demographic characteristics; (6) only controlled for geographic characteristics; (7) all control variables included.

Appendix D.3. Further Robustness Checks

Table D.5: Further robustness checks.

	Δ mobility '20 modified	Δ mobility '22 modified	Δ mobility '22 −' 20 modified	Δ mobility ≥ 50 Mbit/s	Δ mobility '20 no weights	Δ mobility '22 no weights
	(1)	(2)	(3)	(4)	(5)	(6)
digitalisation						
× (1) 1st lockdown	1.900***	0.838*	0.0639	0.193*	2.120**	2.032***
	(3.55)	(2.20)	(0.23)	(2.46)	(3.24)	(3.56)
× (2) 1st open period	-0.210	-0.831+	-0.633+	-0.0456	-1.539*	-1.503*
	(-0.33)	(-1.68)	(-1.72)	(-0.47)	(-2.00)	(-2.00)
× (3) 2nd lockdown/ 1st WFH o.	-0.711	-0.922*	-0.544	0.0149	-1.471*	-1.249+
	(-1.26)	(-2.05)	(-1.60)	(0.19)	(-2.31)	(-1.93)
× (4) 2nd open period	-0.359	-1.051+	-0.773	-0.133	-2.259*	-2.132*
	(-0.44)	(-1.65)	(-1.61)	(-1.16)	(-2.48)	(-2.28)
× (5) 2nd WFH obligation	-0.821	-0.711	-0.324	-0.171+	-2.203**	-1.685*
	(-1.14)	(-1.28)	(-0.74)	(-1.89)	(-3.03)	(-2.25)
× (6) post-pandemic	0.700	0.266	-0.00608	0.0445	-0.425	0.177
	(0.65)	(0.37)	(-0.01)	(0.41)	(-0.47)	(0.19)
year-month fixed effects	x	x	x	x	x	x
district-level fixed effects	x	x	x	x	x	x
pandemic controls	x	x	x	x	x	x
socioeconomic controls	x	x	x	x	x	x
infrastructure controls	x	x	x	x	x	x
demographic controls	x	x	x	x	x	x
geographic controls	x	x	x	x	x	x
observations	433999	433999	433999	433999	433999	433999
R^2	0.619	0.619	0.619	0.619	0.558	0.558

Notes: Equation 1 estimated using OLS. t statistics in parentheses. Clustered standard errors. $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Observations weighted by population size if not stated otherwise. The time frame is split into different phases as presented in Figure 3. The pre-Covid-19 phase is used as a reference period. Models are estimated with all control variables. Fixed effects for every phase are additionally included. (1) All firms are considered when calculating the average degree of firm digitalisation in a district, i.e., firms with no available website are set to zero; the indicator is calculated for digitalisation in 2020; (2) same modification but the indicator is calculated for digitalisation in 2022; (3) change in a district's degree of digitalisation is calculated by subtracting the modified indicators for 2020 from the modified indicator for 2022; (4) firm digitalisation is excluded and coefficients for broadband availability are used as a proxy for effects of household digitalisation over time and displayed; (5) - (6) firm digitalisation is calculated for 2020 and for 2022 as in the main analysis, but observations are not weighted by population size.

Appendix D.4. Firm-level Link

To analyse the link between firm digitalisation and the share of employees that work from home, we estimate the following model using MIP 2021 data (Rammer et al., 2021):

$$\begin{aligned}\text{WFH share}_{j,t} = \alpha + \beta_d\, \text{digitalisation}_j^{2020} + \beta_{ld}\, \text{lockdown}_t \\ + \beta_{dld}\, \text{digitalisation}_j^{2020} * \text{lockdown}_t^p + u_{j,t}.\end{aligned} \tag{D.1}$$

Digitalisation is considered for firm j at time t, which can either be the time before the first lockdown (January/February 2020) or a lockdown period. p denotes the considered lockdown, which can either be the first or second one. Results are displayed in Table D.6.

Table D.6: Link between firm digitalisation and WFH at the firm level.

	dependent variable: WFH share			
	(1)	(2)	(3)	(4)
digitalisation (Jan '20)	0.729	0.634	0.624	0.522
	(1.45)	(1.30)	(1.33)	(1.16)
1st lockdown	13.47*	13.47*		
	(2.33)	(2.22)		
2nd lockdown			15.72*	15.71*
			(2.57)	(2.51)
digitalisation (Jan '20) × 1st lockdown	6.364*	6.361*		
	(2.30)	(2.19)		
digitalisation (Jan '20) × 2nd lockdown			7.022*	7.017*
			(2.53)	(2.47)
constant	-0.999	1.196	-2.121	-0.268
	(-0.15)	(0.20)	(-0.31)	(-0.04)
ln(sigma)	2.990***	2.977***	3.012***	3.000***
	(7.00)	(6.63)	(7.75)	(7.54)
industry	x	x	x	x
federal state		x		x
log-likelihood	-18466.7	-18392.3	-18297.7	-18225.1
observations	6028	6028	6028	6028

Notes: Equation D.1 estimated using an interval-censored regression model. Coefficients can be directly interpreted (see Wooldridge, 2002). Sigma is comparable to the standard error of an OLS estimate. t statistics in parentheses. Clustered-standard errors at the firm level. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Digitalisation is standardised with respect to the firm sample. (1) first lockdown only controlling for different industries; (2) first lockdown controlling for different industries and federal-state fixed effects; (3) second lockdown only controlling for different industries; (4) second lockdown controlling for different industries and federal-state fixed effects.

Furthermore, we analyse whether our web-based firm digitalisation indicator can be associated with a greater likelihood that a firm increased its digital products, services, and sales channels with the onset of the Covid-19 crisis based on the MIP 2021. To this end, we fit the following linear model:

$$\text{e-commerce}_j = \alpha + \beta_d \,\text{digitalisation}_j^{2020} + u_j. \tag{D.2}$$

The increase in digital business activities is denoted by the binary variable *e-commerce*. Results are displayed in Table D.7:

Table D.7: Link between firm digitalisation and increased e-commerce activity at the firm level.

	dependent variable: increased e-commerce	
	(1)	(2)
digitalisation (Jan '20)	0.0723***	0.0717***
	(7.54)	(7.42)
constant	0.665*	0.702*
	(2.11)	(2.25)
industry	x	x
federal state		x
R-squared	0.0661	0.0760
observations	3014	3014

Notes: Equation D.2 estimated using OLS. t statistics in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Robust standard errors. Digitalisation is standardised with respect to the firm sample. (1) only controlled for different industries; (2) controlled for different industries and federal-state fixed effects.

Appendix D.5. Link to a district's WFH potential

Table D.8: Equation C.1 with digitalisation replaced by a district's WFH potential. Only daytime mobility changes are considered.

	dependent variable: Δ mobility	
	(1)	(2)
WFH potential	-0.506**	-0.271
	(-2.93)	(-1.50)
digitalisation (Jan '20)		-1.593**
		(-2.78)
constant	27.41	14.41
	(0.57)	(0.30)
year-month fixed effects	x	x
socioeconomic controls	x	x
infrastructure controls	x	x
demographic controls	x	x
geographic controls	x	x
observations	433999	433999
adjusted R^2	0.452	0.454

Notes: Equation C.1 estimated using OLS and all control variables. t statistics in parentheses. Clustered standard errors. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Observations are weighted based on their population size. (1) Equation C.1 estimated for daytime mobility with digitalisation replaced by a district's WFH potential; (2) Equation C.1 estimated for daytime mobility with digitalisation and a district's WFH potential included.

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