International Inequalities Institute

WORKING PAPER 136

The spatially uneven diffusion of remote jobs in Europe

Davide Luca
University of Cambridge

Cem Özgüzel
Paris School of Economics

Zhiwu Wei
University of Cambridge

APRIL 2024

Davide Luca
University of Cambridge

Cem Özgüzel
Paris School of Economics

Zhiwu Wei
University of Cambridge

In addition to our working papers series all these publications are available to download free from our website: www.lse.ac.uk/III

For further information on the work of the Institute, please contact the Institute Manager, Liza Ryan at e.ryan@lse.ac.uk

International Inequalities Institute
The London School of Economics
and Political Science, Houghton Street,
London WC2A 2AE

E Inequalities.institute@lse.ac.uk
W www.lse.ac.uk/III
@LSEInequalities

LSE International Inequalities Institute

Short sections of text, not to exceed two paragraphs, may be quoted without explicit permission provided that full credit, including © notice, is given to the source.

© Davide Luca, Cem Özgüzel, Zhiwu Wei. All rights reserved.

The spatially uneven diffusion of remote jobs in Europe*

Davide Luca,† Cem Özgüzel,‡ Zhiwu Wei§

Abstract

The paper maps the spatially uneven diffusion of working from home across 30 European countries during the COVID-19 pandemic. We summarise the determinants of remote working and show that its uptake was lower than in the US, and substantially uneven across/within countries, with most remote jobs concentrated in cities and capital regions. We then apply a variance decomposition procedure to investigate whether the uneven distribution of remote jobs can be attributed to individual or territorial factors. Results underscore the importance of composition effects as, compared to intermediate-density and rural areas, cities hosted more workers in occupations/sectors more amenable to working remotely. Overall, findings highlight how working from home is unlikely to substantially alter the current patterns of spatial inequality between core urban areas and peripheral rural regions.

Keywords: Work from home; remote work; telework; COVID-19; spatial inequality; Europe

JEL Codes: I18; J20; O52; P25

* The authors are grateful to Rudiger Ahrend, Nadim Ahmad, David Burgalassi, Jasper Hesse, Ana Moreno-Monroy, Michelle Mashalian, Marcos Diaz-Ramirez, Dan Nixon, Franziska Sielker, Alison Weingarden, Paolo Veneri, Wessel Vermeulen and participants at the University of Cambridge Land Economy's brownbag seminar and 2022 Early Career Conference, the OECD workshop on 'The geography of remote work', the 2022 RSAI-BIS annual conference, the 2022 ERSA annual conference, the IAB/ZEW workshop on 'Spatial dimensions of the labour market – megatrends in times of COVID' for help and suggestions. All errors and omissions are our own.

† Department of Land Economy, University of Cambridge, Cambridge, UK; International Inequalities Institute, London School of Economics and Political Science, London, UK; dl622@cam.ac.uk.

‡ Organization for Economic Cooperation and Development, Paris, France; Paris School of Economics, Paris, France; Sorbonne Economics Centre, Paris, France, cem.ozguzel@oecd.org.

§ Department of Land Economy, University of Cambridge, Cambridge, UK, zw387@cam.ac.uk.

Introduction

The COVID-19 pandemic has led to a dramatic acceleration in the expansion of remote work across many advanced economies. The International Labour Organisation (ILO) describes remote work as any "situation where the work is fully or partly carried out on an alternative worksite other than the default place of work" (ILO, 2020, p. 5). Alternative worksites include coworking spaces, cafes, etc. but – most often – workers' own residence.

Because of this, there has been a growing debate on the implications of working from home (WFH, by which we mean both fully remote and hybrid work) for the geography, real estate markets, and productivity of large cities. Similarly, there has been substantial debate on the extent to which remote work may lead to a structural relocation of workers and advanced economic activities from core urban centres towards less densely populated areas (Nathan & Overman, 2020; Florida et al., 2021; Glaeser, 2022; Grabner & Tsvetkova, 2022; Fiorentino et al., 2022; Crescenzi et al., 2022; Nathan, 2023), especially when work is done fully remotely. While there is a growing number of studies uncovering the geography of working from home in the US (Althoff et al., 2022; Ramani & Bloom, 2021), the cross-country comparative empirical evidence from other OECD countries is however scarcer.

Addressing this gap is also important from a policy perspective, as it will allow better understanding what factors are associated with WFH and may hinder achieving the maximum net potential benefits associated with remote work, especially in areas where its uptake is still limited (Eurofound, 2020; European Commission, 2021; OECD, 2020a, 2021c). There is still ongoing debate on the effects of remote work for productivity. Recent studies for example argue that reduced face-to-face interaction may have negative effects on the productivity of high-skill workers and may reduce innovation (Brucks and Levav, 2022). Some studies, by contrast, challenge such views (e.g., Huggins & Thompson, 2022). Overall, there is a growing consensus on how, in the future, the share of work done at least in part remotely will be higher than pre-covid (Aksoy et al., 2022, Bick et al., 2023), and how new forms of work will likely influence the evolution of regional development trajectories (Stantcheva, 2022).

We contribute to the literature by: (a) offering the first comprehensive cross-country investigation of the new geography of working from home across all the European Union (EU) 27 Member States plus Norway, Switzerland, and Iceland; (b) rigorously measuring the extent to which the geographically uneven uptake in WFH can be explained by composition or contextual factors.

The first part of the article provides systematic descriptive evidence on the new geography of remote jobs across the regions and cities of Europe. Special attention is devoted to exploring the geographical and sectoral heterogeneity in the extent to which remote work has increased during the pandemic. To do so, we leverage microdata from the annual waves of the EU Labor

Force Survey (EU-LFS) carried out in 2019, 2020 and 2021. With over 1.5 million respondents in 2019, around 1.2 million in 2020, and around 1.1 million in 2021, the Survey provides a large and geographically representative sample size.

Findings suggest that the average uptake across Europe was lower than in the US (cf., Althoff et al., 2022), and was markedly uneven across and within European countries. Most places with higher levels of remote work before the pandemic also experienced a fastest uptake afterwards. Moreover, on average, workers living in capital regions and urban centres experienced the highest remote work uptake. Furthermore, the uptake was particularly strong in certain areas such as capital regions where it quadrupled, increasing from 6% to 22% during the same period. More generally, between 2019 and 2021, the share of remote workers more than tripled in cities, while it only doubled in towns and semi dense-areas and rural areas. These findings are consistent with recent theoretical contributions. Some scholars have indeed argued that the 'work-from-home revolution' will not significantly alter the economic geography of the global city system (Florida, Rodriguez-Pose, Storper, 2023) nor lead to a 'big city exodus' (Nathan & Overman, 2020) but, instead, will trigger a redistribution of economic activities and workers from city centres to large cities' hinterlands (Bond-Smith & McCann, 2022; Gokan et al., 2022; Mariotti, 2021). While our main empirical focus is on survey respondents who "mostly" work from home, the patterns we uncover are similar when replicating the analysis for respondents who "sometimes" work from home.

Second, the paper explores the drivers of WFH uptake. Drawing on the literature on shocks and regional resilience (cf. Crescenzi et al., 2016), we broadly identify three main sets of conditions potentially influencing the spread of WFH: compositional, contextual, and societal factors. Compositional determinants relate to the demographic/sectorial structure of local and regional economies. Contextual factors refer to the place-specific territorial conditions in which local and regional agents are situated, and which may enable/inhibit workers to switch to remote work. Finally, societal factors are those broader (national) conditions within which local and regional agents are situated.

While the share of remote workers across all European regions rose on average from 5.4% in 2019 to 14% in 2021, the increase was uneven across European countries, reflecting pre-COVID cross-country differences and, as expectable, government lockdown policies during the pandemic.

Confirming international evidence, the results highlight how the workers who have adopted to remote work tend to be older, self-employed, and with higher levels of formal education. They also tend to work in information and communication, financial and insurance, education, professional, scientific, and technical sectors and in occupations such as managers, professionals, technical and associate professionals. These sectors and occupations are in line with those identified by the literature with relatively high 'teleworkability' index (e.g., Sostero et al., 2020; Barbieri, Basso, Scicchitano, 2022). Unexpectedly, the results do not point to significant gender differences in remote work uptake during the pandemic. At the territorial level, findings also show that regional higher internet speed and higher excess mortality rates were significant predictors of the likelihood of working remotely in the first year of the pandemic, but their explanatory power and significance comparatively decrease in 2021.

The article subsequently employs the variance decomposition procedure proposed by Gelbach (2016) to identify the relative role of individual vs territorial factors in explaining the remote work uptake gap we identify between cities and other areas. Controlling for country-specific heterogeneity, both individual and territorial regressors are relevant predictors of remote work uptake. At the same time, the variance decomposition analysis suggests that workers and industrial composition play a larger role than territorial factors. Controlling for country-specific time trends, the individual characteristics of the respondents can explain about 87.6% of the overall gap in remote work between cities and other areas in 2020, while contextual territorial factors can explain only about 12.4% of such variation.

Overall, the paper aims to contribute to the growing literature on remote work. There is substantial related research on the territorial spread of COVID-19 across Europe (inter alia: Ascani et al., 2020; Corradini et al., 2022; Diaz-Ramirez et al., 2022). There is also a growing amount of research focused on the micro-scale, exploring how COVID-19 and remote work uptake have been affecting the structure of cities in specific countries (inter alia: Brail & Kleinman, 2022; De Fraia et al., 2022; Delventhal et al., 2022; Kyriakoupoulou & Picard, 2023; Legeby et al., 2023). Yet, we still lack systematic, cross-country empirical evidence on the territorial diffusion of working from home across the whole of Europe. This is only partly related to the effects of the pandemic, and better understanding the new geography of remote jobs across Europe can set the stage for other contributions in this special issue.

The remainder of the paper is structured as follows. The second section reviews the existing literature on the nature and determinants of remote work uptake. The third section discusses the data sources and describes our measures of remote work and their validity. Next, the fourth section documents the changes in the geography of remote work throughout the pandemic across Europe. The fifth section empirically tests, for European workers, the extent to which potential enabling/inhibiting factors explain the likelihood of working remotely during the pandemic. The last section concludes.

COVID-19 and the uneven expansion of remote work

The outbreak of the COVID-19 pandemic has led to a dramatic acceleration in the expansion of work from home, which can be fully remote, or hybrid. In the US – one of the countries where the new emerging patterns of work have been studied the most – around one third of all workers took up remote working during the first months of 2020 (Yang et al., 2022). In the United Kingdom, by April 2020, the share of individuals working remotely increased by around 20 percentage points compared to the pre-pandemic levels (OECD, 2021b). Similarly, between February and December 2020 Australia witnessed a 15 percent point increase (OECD, 2021b). Noteworthy rises in remote work uptake have also been recorded across emerging and middle-income countries (cf. Gottlieb et al., 2021).

Various factors have been linked to the territorial diffusion of remote work. Drawing on the literature on shocks and regional resilience (cf. Crescenzi et al., 2016), we broadly identify three main sets of conditions potentially influencing the spread of WFH: compositional, contextual, and societal factors. Compositional determinants relate to the demographic/sectorial structure of local and regional economies. Contextual factors refer to the place-specific territorial conditions in which local and regional agents are situated, and which may enable/inhibit workers to switch to remote work. Finally, societal factors are those broader (national) conditions within which local and regional agents are situated. The following sub-sections discuss each hypothesis in detail.

Societal conditions: the role of lockdown policies and general employment regulation

First and foremost, the acceleration in the expansion of remote work was linked to the outbreak of COVID-19, and to the different lockdown policies implemented by governments. These measures diverged significantly across countries, and around the world have been shown to be positively associated with WFH levels (Aksoy et al., 2022). Beyond lockdown measures, country-specific employment regulations and general social acceptance of working remotely instead of working in the office are also critical determinants in the spread of WFH.

Remote work and sectoral and workforce composition

Remote work uptake may differ across cities and regions as these places do not host the same type of sectors and/or workers. For example, professional and management jobs are generally more amenable to remote work than other occupations (OECD, 2021a). Consequently, while the places with a higher concentration of low-skilled jobs are less likely to switch to remote work, others where skilled tradeable services or industries (e.g., information, finance and insurance, professional services, and management) are located will find it easier to adapt (Althoff et al., 2022; Adams-Prassl et al., 2022). The sectors and occupations with relatively high 'teleworkability' index have been identified by the literature, including Information and Communication, Finance and Insurance, Real Estate, Professional services, teachers, managers, keyboard operators (e.g., Sostero et al., 2020; Barbieri, Basso, Scicchitano, 2022). Since such industries and jobs tend to concentrate in cities, these places may be more suitable for switching to remote work.

Remote work may also correlate with individual characteristics such as education, gender, or age of workers. For example, individuals with higher levels of formal education are more likely to work in occupations that are more amenable to remote work (Adams-Prassl et al., 2022; OECD, 2021a). Studies also found that self-employees are more willing to work remotely (Eurofound, 2020).

The evidence on the relationship between gender and remote work potential is mixed. Drawing on survey data from the US and the UK, Adams-Prassl et al. (2022) suggest that women are less likely to work in occupations and sectors that are amenable to remote work. For example, women are more likely to be over-represented in non-tradeable service sectors such as hospitality and health, while being under-represented in managerial roles. However, in a cross-country study, Sanchez et al. (2020) do not find such a clear pattern. The authors suggest that women are less likely to be employed in jobs amenable to remote work in Turkey, while the opposite is true for Brazil, Mexico, and the EU, while there are no clear patterns in India. Similarly, Sostero et al. (2020) also claim the absence of any difference across genders in terms of remote work across the EU. However, women have historically been more likely to stay home for child and family care needs, especially in countries with more traditional and patriarchal social norms. During the pandemic, women may have used remote work more than men to 'cushion' the sharp reduction in childcare support associated with lockdown measures (Alon et al., 2020). Overall, the association between remote work and gender remains unclear.

The evidence on the importance of age also remains inconclusive. While older workers may on average, possess weaker information and communication technology (ICT) skills, older workers are more likely to hold senior managerial positions, which are by nature more amenable to remote work (Dingel & Neiman, 2020; Sanchez et al., 2021; OECD, 2021a).

Contextual factors and remote work uptake

Remote work requires a suitable context, i.e., local conditions. First and foremost, many occupations that are in theory teleworkable require a fast and reliable internet connection. Internet has allowed many jobs to be conducted remotely, even in sectors where up to recently physical presence was deemed essential e.g., in education, health, or tradeable services. Similarly, research shows that broadband connectivity allows small towns near larger metropolitan centres to 'borrow size' and reap the advantages of larger agglomerations (de Vos et al., 2020).

Yet, there are significant differences in the digital infrastructure both within and across many countries (Vilhelmson & Thulin, 2001; OECD, 2022). For example, in 2020, the internet speed in cities was on average 23% faster than national averages, while speed in towns/semi-dense areas and rural areas was respectively 7% and 30% slower than average.

Second, the suitability of home conditions for remote work can also matter. Cuerdo-Vilches et al. (2021) suggest that having a more spacious home with a dedicated workspace, or good environmental quality are associated with higher uptake of remote work. In most OECD countries, these factors are usually more easily available in less dense regions and outside of large cities, where real estate prices are higher. There is however also a strong argument to assume that large cities may host more remote workers, especially when this is hybrid and involves at least a few days in the office. Bond-Smith and McCann (2022) focus on the costs and frequency of commuting as the key element to understanding how WFH will impact on cities. They suggest that the reduction in the frequency of commuting reduces its opportunity costs, and hence makes large urban agglomerations and their hinterlands more appealing, i.e., it increases the job matching opportunity for hybrid workers in large cities and enlarge their hinterlands, potentially encroaching on the local hinterlands of smaller cities and towns. As the two authors suggest, compared to North America this may be particularly true in Europe, where cities tend to be much more closely located.

Third, the decision to take up remote work may be closely related to the local impact of the pandemic and its heterogeneous geographies (inter alia: Ascani et al., 2020; Corradini et al., 2022; Diaz-Ramirez et al., 2022), as workers living in areas hit more severely by the pandemic might have been more willing – or forced – to stay at home to avoid the virus (Ramírez et al.,2022). The severity of the pandemic, captured through the excess mortality, was strikingly uneven across the subnational regions of OECD member states (Diaz-Ramirez et al., 2022). Because of higher population density and higher risks of contagion, urban areas have historically tended to be more negatively affected by pandemics. One could hence also assume that higher WFH rates in cities during the COVID-19 pandemic may be driven by higher fear of contagion among urban dwellers (cf. Eurofound, 2020).[5]

In summary, differences in uptake may be driven by different sets of factors. The remainder of the analysis will test these alternative hypotheses empirically.

Data and the measurement of remote work across Europe

[5] We thank one anonymous referee for highlighting this point.

Overview of the European Union Labour Force Survey and the empirical sample

The empirical analysis draws on data from three waves of the annual EU Labour Force Survey carried out in 2019, 2020 and 2021. The EU-LFS is conducted by the national statistical institutes of EU member states (plus a few non-EU countries). Each national survey is a cross-sectional household survey meant to be representative of the entire workforce at the "Territorial Level 2" (TL2) level,[6] and follows common Eurostat classifications as well as the ILO guidelines.

This paper restricts the focus to all employees and self-employed individuals aged 17 and over living across all the 27 EU Member States, plus Norway, Switzerland, and Iceland.[7] The paper excludes workers employed in agriculture, forestry and fishing, and armed forces. It does so because in these sectors the concept of remote work has limited relevance, and it is difficult to distinguish between working remotely and working in the "usual" workplace.

Overall, the available sample covers more than 1.5 million workers for the 2019 wave, around 1.2 million workers in 2020, and around 1.1 million respondents in 2021. The dataset also provides survey weights, and these are used throughout the analysis.

The measurement of remote work

Remote work can include working-from-home (WFH), as well as working from other sites such as co-working spaces, cafes, etc (see Mariotti, Di Marino, Bednar, eds., 2023, and Mariotti, Capdevila, Lange, 2023, for detailed descriptions of coworking and other new working spaces). The current research focuses on working-from-home (WFH), i.e., work that takes place fully or partly within the worker's own residence.[8] This is done on two grounds. First and foremost, the analysis is constrained by data availability, as the information available in the EU-LFS focuses specifically on WFH. Second, despite the growing relative importance of coworking spaces, we believe that their absolute share as workplaces is still modest overall.

[6] The EU-LFS is representative at the Eurostat NUTS2 level. For most European countries, NUTS2 regions correspond to the OECD TL2 classification. In Belgium, France, and Germany, however, NUTS2 do not exactly correspond to TL2 regions, but are a tier between TL2 and TL3. In these cases, the current analysis retains the NUTS2 structure. Furthermore, in the cases of Austria, Netherlands, Iceland, and Croatia, the survey data is only available at country (TL1) level.

[7] The EU Member States included in the study are Austria, Bulgaria, Belgium, Croatia, Cyprus, Czechia, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden.

[8] It is important to note again that WFH is not completely equivalent to remote work because home, for some jobs such as those carried out by home-based workers, can be the default place of work. Due to data limitations, we exclusively use WFH to measure remote work. Moreover, we also distinguish WFH from telework which refers to situations where workers 'use information and communications technology (ICT) or landline telephones to carry out the work remotely', while there is an overlap between telework and WFH, i.e., telework from home (ILO, 2020). WFH can be adopted in a full or hybrid mode (hybrid working refers to the situations where workers spend some of their time in the default place and some at home), depending on the frequency with which workers carry out WFH, as described below.

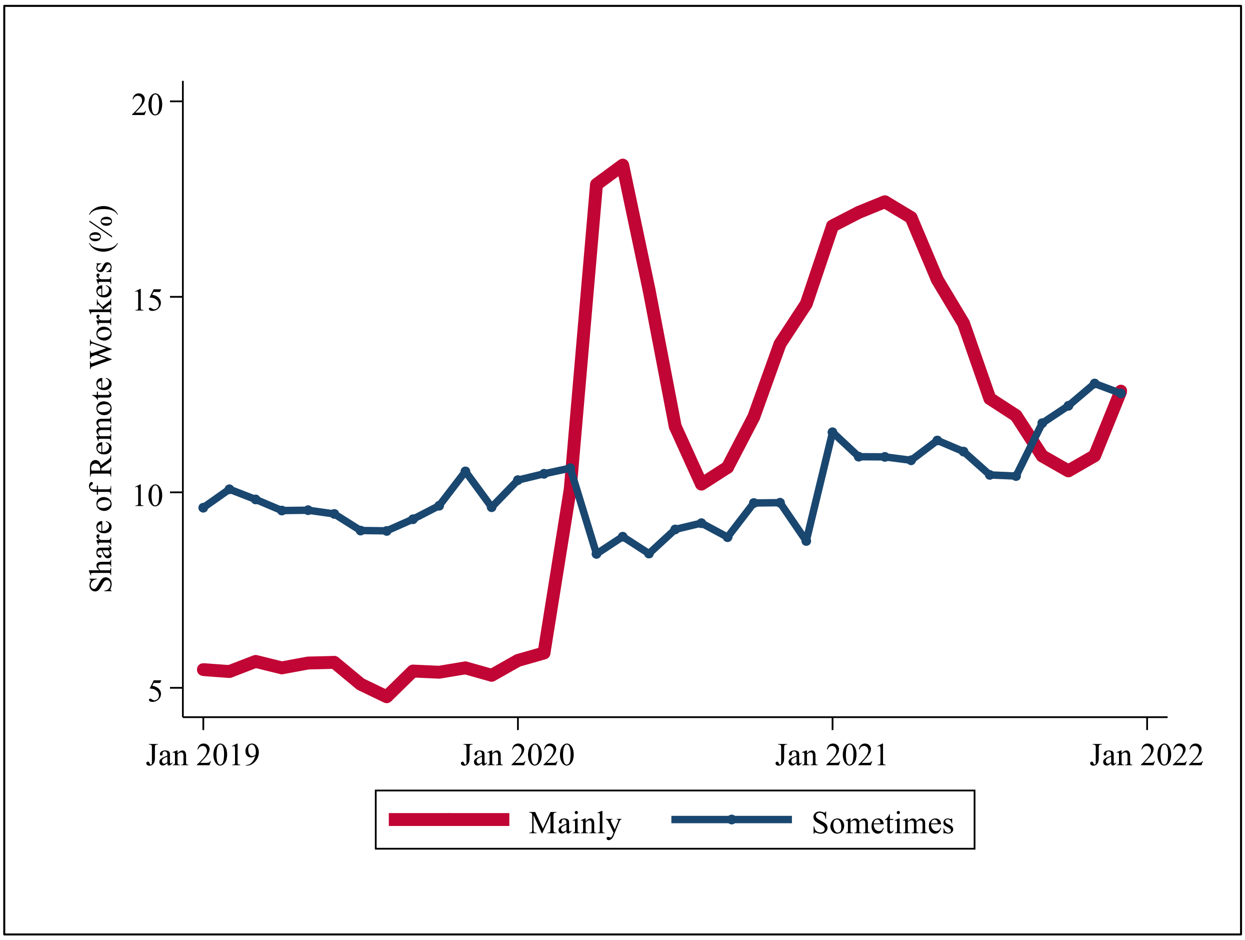
Work can be carried out fully remotely, or in a hybrid way. The survey records whether respondents: (1) “mainly work at home”; (2) “sometimes work at home”; (3) “never work at home”.[9] While it is difficult to clearly ascertain if respondents who “mainly” work from home do so entirely, as opposed to “sometimes”, the current analysis assumes that the formers are “full-time remote workers”, while the latter are more likely involved in “hybrid work”.[10] Figure 1 plots the shares of workers who “mainly” or “sometimes” worked remotely during the period spanning from January 2019 to December 2021 (the most recent point for which data is currently available).

As the figure shows, the share of respondents who “sometimes” work remotely has only moderately increased. By contrast, the share of those “mainly” working remotely has almost tripled after the onset of the pandemic, rising from 5.5% in 2019 to 14% over 2021, while peaking at 18.5% in May 2020. Although it is difficult to offer an exact international comparison because of differences in how surveys identify remote work, the share of home workers from the EU-LFS seems overall lower than in the US where, according to the US Current Population Survey (sample of around 60,000 individuals across all the American states) working from home peaked in May 2020 at around 40% (cf. Althoff et al., 2022). Even at the peak of the pandemic during the spring of 2020, across Europe the share of those “mainly” working from home was below 20%.

[9] This variable refers to the main job of the respondent. Within a reference period of four (to twelve) working weeks preceding the end of the reference week, “mainly” denotes working at home at least half of the time; “sometimes” denotes working at home less than half of the time; “never” denotes working at home on no occasion.

[10] It is important to stress that the Survey does not offer more detailed measures of how much time is spent at home as opposed to the workplace. It is hence impossible to measure in a more precise way what “mainly/sometimes” working from home imply. Similarly, it is not possible to identify workers who work remotely but not at home.

Figure 1. The evolution of hybrid and remote work across Europe



Note: This figure plots shares of remote workers by remote work frequency for 30 European countries between 2019 and 2021. In most countries, the share of workers who "mainly" worked remotely increased significantly, whereas the share of workers who "sometimes" worked remotely has remained relatively stable. This plot, as well as all other pieces of analysis, uses as customary survey weights.
Source: European Union Labour Force Survey (EU-LFS).

Appendix A offers a set of additional figures breaking down the overall estimates of Figure 1. For example, the appendix breaks down the aggregate values of Figure 1 into macro-groups of countries distinguishing between Central and Eastern Europe, Western Europe, Southern Europe, and Northern Europe.[11] The results highlight substantial differences across each macro-region, with remote work being more prevalent in Western and Northern European countries. However, the trends are similar across the continent, and confirm how the increase primarily involved respondents "mainly" working from home (cf. Appendix Figures A.1 and A.2). To study how the pandemic influenced the work mode change, we therefore focus on those "mainly working

[11] Countries in Central and Eastern Europe include Poland, Hungary, Romania, Czechia, Slovakia. Countries in Western Europe include Germany, Netherlands, Belgium, Luxembourg, Austria, Switzerland, France. Countries in Southern Europe include Portugal, Spain, Italy, Greece, Slovenia, Croatia, Cyprus, Malta. Countries in Northern Europe include Iceland, Norway, Sweden, Finland, Ireland, Estonia, Latvia, Lithuania, Denmark.

from home". (Robustness checks will show that results are robust when also considering respondents "sometimes" working remotely.)

Appendix Figure A.6 shows the occupations and sectors with the highest remote work uptake, comparing the share of actual remote workers in each year across 720 industry-occupation pairs. The adoption of remote work has been highest in industries such as "information and communication", "finance and insurance", "professional, scientific and technical services", and "education", and among occupations such as managers, professionals, and associate professionals. As one would expect, the combination of industry and occupations is also relevant. For example, while before the pandemic differences were modest, we find that ICT professionals had higher propensity to work from home than teaching professionals during the pandemic.

To ascertain the extent to which our measure of *actual regional remote work* correlates to measures of regional remote work *potential*, we calculate a measure of potential following the approach of Dingel & Neiman (2020) for the US. (See Appendix B for details on how we calculate it.) The two measurements are closely linked, and the correlation between the two increases during the pandemic. (See Appendix C for the correlation results.)

Other individual-level variables

For each respondent, the EU-LFS provides a comprehensive set of individual details such as age, educational attainment, engagement in economic activities (or industries), occupation, employment status, gender, personal relationship status, being a parent of children under 15 years old. Economic activities are classified according to the Nomenclature of Economic Activities (NACE), while occupations are classified following the International Standard Classification of Occupations (ISCO-08). For reason of space, the paper reports only the results for the industries and occupations which, according to the analysis reported in Appendix Figure A.6, were mostly associated with remote work uptake. These industries are "information and communication", "finance and insurance", "professional, scientific and technical services", and "education", while the occupations include managers, professionals, and associate professionals.[12] Finally, the EU-LFS also reports the degree of urbanisation of where each respondent lives.[13]

[12] Results for any other industries and occupations not explicitly reported in the paper are available on request.

[13] The surveys report the degree of urbanisation of the place of residence rather than of the place of work (cf. https://ghsl.jrc.ec.europa.eu/degurba.php, accessed on 14 February 2023). This is a limitation since respondents may live outside of cities but commute to them to work. Section 4 provides a discussion of how such a limitation may affect the results of the analysis.

Appendix D.1 provides a table with the detailed breakdown of the average shares for each of the variables included in the analysis, distinguishing between the 2019, 2020 and 2021 EU-LFS waves, while highlighting the survey response rate for each variable.

Territorial level variables

Importantly, the EU-LFS matches each respondent to their TL2 region of residence.[14] It is therefore possible to measure the remote work uptake at the regional level and match the EU-LFS data to other territorial information. It is worth stressing that measuring the location of workers at the place of residence – rather than the place of work – help minimising any potential measurement error otherwise linked to workers who, during the pandemic, might have moved out of cities while continuing to work for an employer based in urban centres.

Following the conceptual framework, the analysis includes regional-level variables on internet speed deviation (relative to national averages) from the OECD Regional Database, and data on excess mortality from Ramírez et al. (2022). Internet speed deviation data are collected quarterly for each region and, within each subnational region, are disaggregated by degree of urbanisation.[15] Excess mortality data measures monthly excess deaths at the regional level in 2020 and 2021 relative to the averages over 2016-19, and is a proxy for capturing the severity of the pandemic in each region.[16] The analysis matches the two regional level variables with the EU-LFS data by region, degree of urbanisation, and time (where applicable).[17] Appendix Table

[14] While for brevity the remainder of the analysis will refer to TL2 regions, it must be remembered that the EU-LFS is available at Eurostat NUTS2 level, which in the cases of Belgium, France, and Germany, do not exactly correspond to TL2 regions. And it is available at TL1 level for Austria, Netherlands, Iceland, and Croatia. It is important to stress that our focus on TL2 (and TL1) is primarily driven by data availability. In an ideal world one could for example explore functional labour market areas, although: (a) finding such data for a comparative cross-country analysis covering 30 countries and including remote work variables is to our best knowledge virtually impossible. (b) Functional labour market units may be endogenous to remote work patterns. Similarly, individual observations are not geo-tagged in the EU-LFS, and we hence cannot work around smaller spatial units. Overall, while our strategy is primarily explained by data availability, we do our best by interacting TL2 (or TL1) regions with degrees of urbanisation. This is the smallest units that we can observe.

[15] In contrast to the EU-LFS, data on internet speed deviation and excess mortality are available at TL1 and TL2 levels. We match 4 TL1 regions for both variables, and 186 TL2 regions for excess mortality. The numbers of TL2 regions matched for internet speed deviation data are 192 (2019), 196 (2020), 193 (2021). Cyprus and Ireland do not have excess mortality information.

[16] We are unfortunately unaware of any cross-country consistent dataset measuring the stringency of government lockdown policies at the subnational level. In absence of such a variable, we include excess mortality as a second-best proxy. It is also worth noting that in all our regressions we include country-by-month fixed effects and, thus, we do capture any stringency measure which is constant across regions of each country. Appendix Figure A.7 plots national monthly excess mortality against the national stringency index on government lockdown policies. While there is no perfect correlation between the two variables, in most countries there is an overall link between the stringent level of governments' responses to the pandemic and excess mortality.

[17] Since internet speed deviation has little variation across quarter, we calculate the annual averages of internet speed deviation and match it with the EU-LFS by region by degree of urbanisation and by year. To capture the pandemic severity across month, we match excess mortality with the EU-LFS by region by month (excess mortality information is not available at the degree of urbanisation level).

D.2 reports key descriptive statistics for the regional-level variables. In 2020, the average monthly excess mortality was 4%, compared to 12.5% in 2021. Across all years, the average internet speed was faster in cities than towns and semi-dense areas, and rural areas. In 2020, internet speed disparities between cities and other areas increased, with cities becoming on average 23% faster than national averages, while towns/semi-dense areas and rural areas were respectively 7% and 30% slower. In 2021, the gap in internet speed increased between cities and towns and semi-dense areas but reduced between cities and rural areas.

The uneven geographical expansion of remote work

This section maps the geographical distribution of remote work uptake in Europe between 2019 and 2021. It first provides a country-level overview, followed by an analysis at the TL2 level, while also distinguishing between areas at different degrees of urbanisation. The evidence shows an overall level of path-dependency in the spread of remote work. The areas with a higher share of remote workers in 2019 have tended to experience a faster uptake during the pandemic. Besides, while almost all areas experienced an increase in the number of remote workers, the uptake has been particularly fast in capital regions and in cities.

Results by countries

Since the outbreak of the pandemic, almost all countries experienced increases in the spread of remote work. However, this increase has been markedly uneven within and across countries. Figure 2 plots the shares of remote workers for each of the 30 countries covered by the data. Countries are ordered vertically by their 2019 shares.

As expectable, across most countries remote work uptake is closely linked to governmental lockdown policies. Appendix Figure A.3 plots the monthly shares of remote workers and the monthly average stringency index across each of the 30 European countries included in the analysis, using the index developed by Hale et al. (2021) to measure the stringency of government lockdown policies during the pandemic.[18] The plots confirm how a majority of countries – such as Austria, Denmark, France, and Germany – experienced a peak in their shares

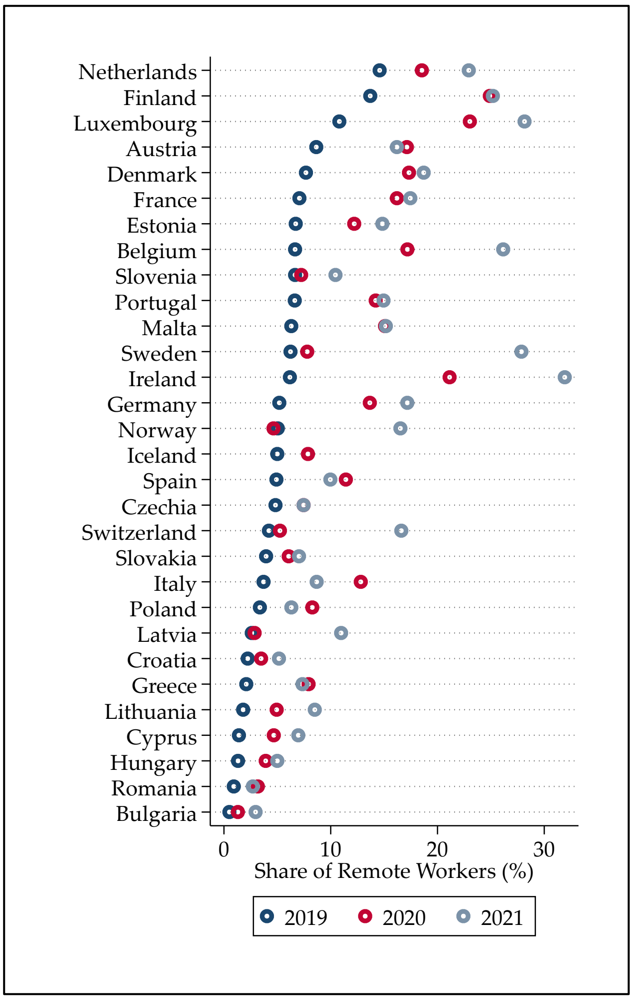
[18] They compute a systematic daily stringency index to record cross-national government responses to the pandemic, accounting for various lockdown measures such as school closings, travel restrictions, financial support, investments in health systems, vaccine policies, etc. Higher values of the stringency index imply that national governments have taken more restrictive measures to contain the spread of the COVID-19 virus.

of remote workers in April/May 2020, when their respective governments imposed the most stringent restrictions.[19]

While the increase in the remote work during the pandemic was uneven across countries, the uptake has generally tended to be stronger in countries with higher pre-pandemic levels. (Two exceptions are Sweden and Ireland which, by 2021, had become two of the countries with the highest incidence of remote work despite lower pre-pandemic levels.) In 2019, the Netherlands had the highest share of remote workers (around 15% of the workforce) while Bulgaria had the lowest incidence (only 1%). In 2021, the highest incidence of remote work was recorded in Luxembourg, Belgium, Sweden and Ireland, all with over 25% of respondents working remotely. (While it is beyond the scope of our current analysis, future comparative work should explore in more depth the national-level policies which may have contributed to this cross-country divergence.)

[19] Appendix Figures A.4 and A.5 replicate the exercise respectively replacing the overall stringency index with two of its sub-components.

Figure 2. Shares of remote workers by country, 2019 to 2021



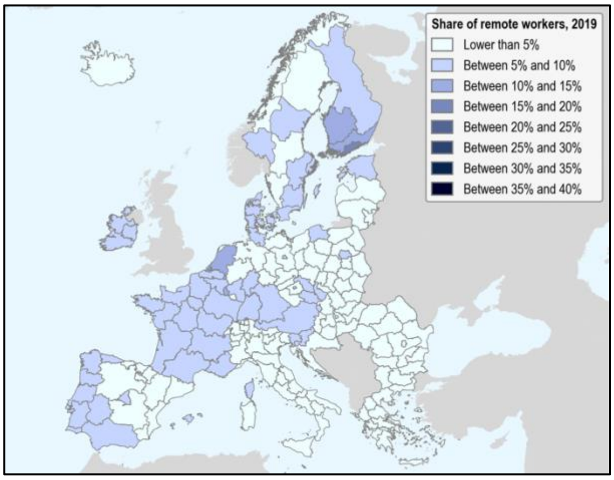
Note: This figure plots the shares of respondents working remotely for 30 European countries. It shows that the shares increased for most countries, and that the increases have tended, in general, to be proportional to initial levels.
Source: European Union Labour Force Survey (EU-LFS).

Results by TL2 regions

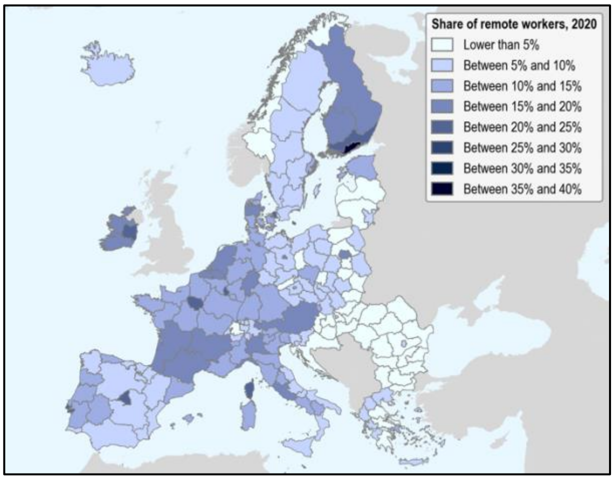
During the pandemic regions diverged in their shift to remote work. Figure 3 maps the high spatial heterogeneity in the rates of remote work uptake.

Figure 3. Regional share of remote workers by TL2 regions, 2019 to 2021

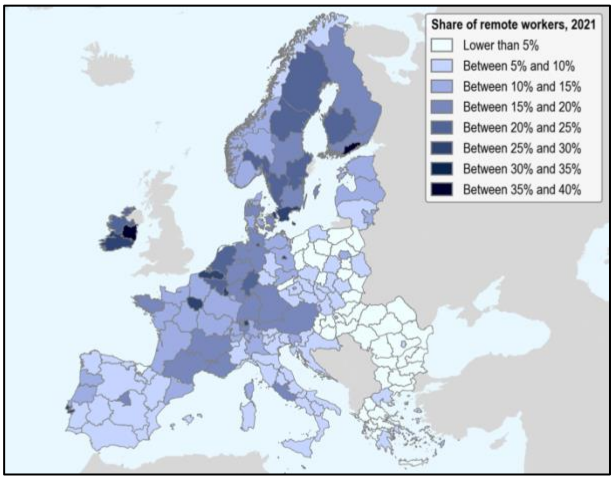
Panel A: 2019



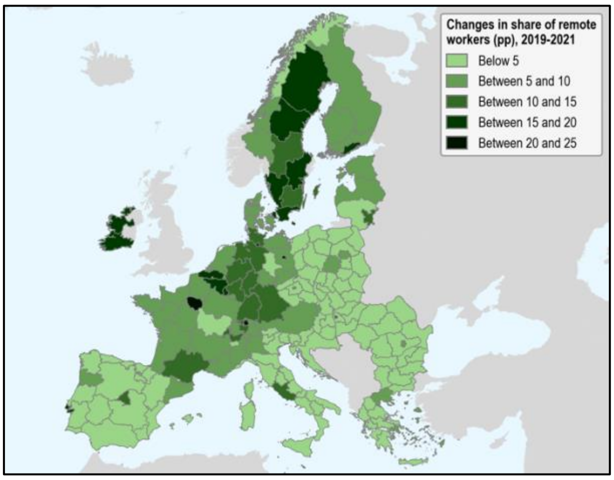
Panel B: 2020



Panel C: 2021



Panel D: Change between 2019 and 2021



Note: This figure plots regional shares of remote workers across TL2 regions, in 2019 (Panel A), 2020 (Panel B), 2021 (Panel C), and changes in absolute percentage points (Panel D). The maps overall show that most regions experienced an increase in remote work. Finland, Western and Southern Europe experienced higher shares of remote workers than Central and Eastern Europe in both years. Furthermore, across most countries the highest increase in remote work uptake occurred in TL2 regions hosting either the capital city, or urban agglomerations. Data for Norway and Iceland is only available for one year, and it is hence not possible to calculate changes in Panel D.
Source: European Union Labour Force Survey (EU-LFS).

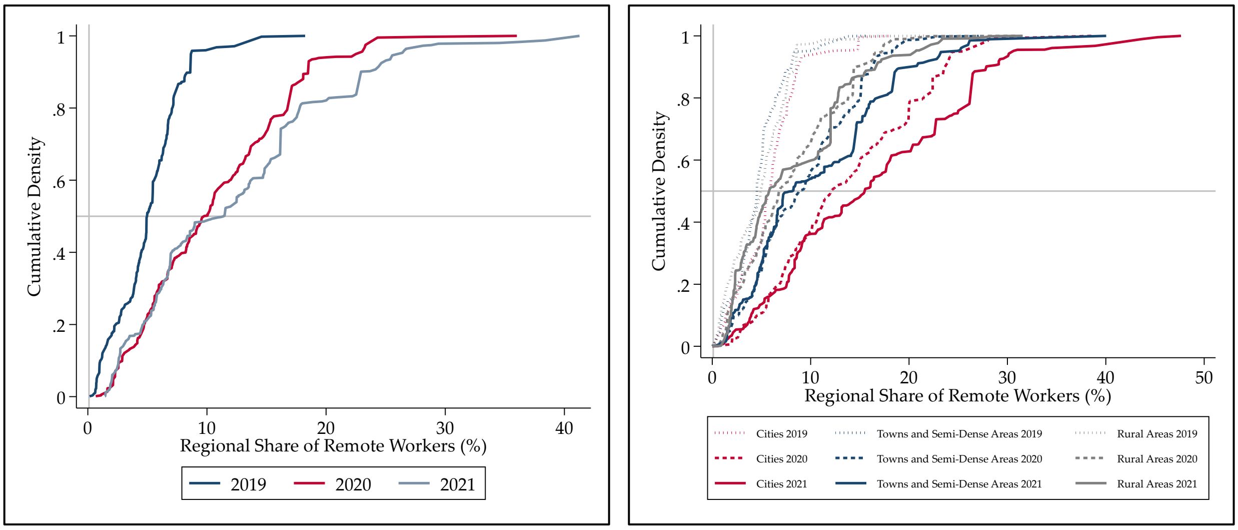
It shows the shares of remote workers across European TL2 regions (except for Austria, Netherlands, Iceland, and Croatia, where subnational information is unavailable) in 2019 (Panel A), 2020 (Panel B), 2021 (Panel C), as well as the changes in absolute percentage points over the three years (Panel D). Before the pandemic, the differences between TL2 regions were modest across the continent. By contrast, by 2021 distinctive patterns had developed. With a few exceptions – e.g., southern France, Northern Sweden, and parts of western Germany – most regions with the highest incidence of remote work at the end of the pandemic were clustered around capital cities, or in regions hosting large urban centres. While the average share of remote workers across the continent increased from around 5% in 2019 to around 14% in 2021, in capital regions it almost quadrupled, growing from 6% in 2019 to around 22% in 2021.[20]

Results by the degree of urbanisation

This final section maps the geographical heterogeneity in remote work uptake distinguishing respondents by their degree of urbanisation. This is possible since the EU-LFS records not only the TL2 region where respondents live, but also whether they live in cities, in towns and semi-dense areas, or rural areas.[21]

Figure 4. Cumulative distribution functions of regional share of remote workers, 2019 to 2021

Panel A: total shares | Panel B: by degrees of urbanisation



Note: This figure plots cumulative distribution functions of regional shares of remote workers. Panel A shows that regional shares of remote workers systematically increased during the pandemic and showed larger regional heterogeneity relative to the pre-pandemic level. Panel B then breaks down the regional-level shares distinguishing between the degree of urbanisation of respondents. The plot shows that, cities have experienced the highest increase in remote work uptake.
Source: European Union Labour Force Survey (EU-LFS).

Figure 4 shows that, while all areas recorded similar levels of remote work prior to the pandemic, since 2020 cities have experienced a markedly higher uptake compared to other areas. Panel A of Figure 4 presents the dispersion in the cumulative distribution function of the regional shares

---

[20] There are some exceptions. Countries such as Germany and Italy, traditionally characterised by the presence of multiple economic core cities, show high levels of remote work uptake also outside of their capital city-region.

[21] The survey unfortunately reports the degree of urbanisation of the place of residence rather than of the place of work. This is a limitation since respondents may live outside of cities but commute to them to work. Such a limitation leads to measurement error. At the same time, measuring the degree of urbanisation at residence level may lead to a downward bias in the urban-rural gap uncovered by the analysis. If, for example, respondents who work in cities but live in rural areas transition to remote work, measuring the degree of urbanisation at place of residence would mean that these respondents would increase the share of workers from rural areas, hence reducing the urban-rural gap highlighted in Figure 7. Overall, an optimal strategy to mitigate these measurement errors would be to have data at the functional urban area (FUA) level. Such data is however not available.

of remote workers. The more vertical the lines are, the more homogeneous all regions are. The figure shows how, over time, all lines shift to the right, suggesting that across all TL2 regions, the shares of 2021 consistently exceeded those of 2019. Similarly, the plot shows how prior to the pandemic the share of remote workers did not exceed 15% in the most extreme cases, with shares below 10% across most regions. By contrast, by 2021 the regional-level shares have become significantly more dispersed, ranging from 2% to over 40%. Panel B then breaks down the regional cumulative distribution functions by the degree of urbanisation. It shows that, in 2019, remote work was only marginally higher in cities (6%) than in towns and semi-dense areas (5%), or in rural areas (5%). By 2021, however, while remote work spread everywhere, cities experienced the fastest surge.

To conclude, most places with higher levels of remote work before the pandemic also experienced a fastest uptake afterwards. Moreover, on average, workers living in capital regions and urban centres experienced the highest remote work uptake.

Individual vs territorial factors and the geography of remote work

The previous section highlighted the uneven geography of remote work uptake. This section aims to test what factors explain such heterogeneity. It does so by analysing the extent to which, holding country-specific heterogeneity constant, the individual and contextual factors identified in Section 3 predict the likelihood of respondents to work remotely during the pandemic. Understanding the relative importance of individual vs territorial factors is essential for designing future policies around WFH. The results suggest that individual remote work uptake is explained by both individual and contextual characteristics. Territorial features such as regional excess mortality from COVID-19 and internet speed partly predict why cities hosted more remote workers than semi-dense and rural areas. However, the worker composition in terms of jobs and sector of employment seems to play a bigger role in explaining remote work uptake.

Empirical model and variables

The analysis adopts the following empirical model:

$$RemoteWork_{ir} = \beta_1 PerChar'_{ir} + \gamma_1 City_{ir} + \gamma_2 RegChar'_{rm} + \delta_r + \alpha_{cm} + \epsilon_{ir}, \qquad (1)$$

where $RemoteWork_{ir}$ is a dummy indicating if individual i in region r works remotely. As the EU-LFS is a repeated cross-sectional survey (i.e., it does not interview the same individuals over time), the regressions are run separately for each of the years 2019, 2020 and 2021.[22]

Although remote work is a binary outcome, the paper applies an Ordinary Least Squares (OLS) estimator (i.e., a linear probability model). This is done as OLS results are easier to interpret. Logit outputs are reported in Appendix Section F and show that the results remain qualitatively unchanged.

The matrix of personal characteristics $PerChar'_{ir}$ is included to test the importance of compositional factors. These characteristics are age groups, educational attainments, one-digit NACE[23] industries, two-digit ISCO-08[24] occupations, full-time employment status, gender, relationship status, and being a parent of children under 15. Each of these personal characteristics is expressed as a dummy variable. Thus, the coefficient on each dummy of $PerChar'_{ir}$ can be interpreted as the difference in remote work uptake relative to the respective reference group.[25]

To test the contextual effect hypothesis, the empirical model first controls for the level of urbanisation of respondents' place of residence. $City_{ir}$ is a dummy indicating if the respondent lives in a city, as opposed to a town and semi-dense or rural area. The coefficient of the $City_{ir}$ dummy can be interpreted as the difference in remote work uptake between workers living in cities and all other areas (towns and semi-dense and rural areas).[26]

The analysis then supplements the EU-LFS survey data with regional indicators. In addition to the time-invariant region fixed effects (FEs) δ_r, which can account for a variety of region-specific idiosyncratic factors (e.g., differences in climate and natural amenities, infrastructure endowment, local government quality, etc.), the matrix $RegChar'_{rm}$ includes two key regional factors: internet speed deviation and excess mortality rates during the pandemic. Internet speed deviation is measured, within each TL2 region, by the degree of urbanisation. It is therefore

[22] Due to the nature of the survey as a repeated cross-section, utilizing the panel dimension to run an individual-level model measuring outcomes in changes rather than levels isn't feasible. Nonetheless, for robustness checks, we pool together data from all three survey waves and run regressions incorporating country-by-year fixed effects and region fixed effects. These results align closely with our baseline estimates for the samples interviewed during the pandemic, as detailed in Appendix Table F.2.

[23] The Nomenclature of Economic Activities (NACE) represents the European statistical classification of economic activities. Cf. https://nacev2.com/en, accessed on 14 February 2023.

[24] This is the International Labour Organisation (ILO)'s International Standard Classification of Occupations. Cf. https://www.ilo.org/public/english/bureau/stat/isco/isco08/, accessed on 14 February 2023.

[25] Reference groups for each variable are as follows: 17-24 years old, lower secondary education level, 'other' industry, 'other' occupation, employee, being employed part-time, male, without partner in the same household, not-having children under 15.

[26] The analysis combines towns and semi dense areas with rural areas because the marginal difference in remote work between the two categories is more modest (cf. Figure 4).

mapped to the EU-LFS by regions by degrees of urbanisation each year. The excess mortality rate captures the local severity of the pandemic and is measured as the regional cumulative increase in mortality every month m compared to the regional average number of deaths in the same month over the period 2016-2019. As such, it is matched to the EU-LFS by TL2 regions and by months. Workers in areas with higher excess mortality rates are expected to be more likely to work remotely.

The regressions include TL2 regional fixed-effects (FEs), which allow comparing individuals living within the same region. Therefore, the coefficients β_1, γ_1 and γ_2 capture the contribution of each factor on the remote work uptake relative to other individuals working *within* the same TL2 region. While the estimation of Equation 1 may still suffer from endogeneity (e.g., because of individual sorting based on unobservable characteristics), the inclusion of regional FEs helps minimise the risk of omitted variable bias which may otherwise seriously undermine the results.[27]

Lastly, the regressions control for country-by-month fixed-effects α_{cm} to account for country-specific societal characteristics and for trends in the evolution of the lockdown measures during the pandemic. ϵ_{ir} is the error term. For all regressions, robust standard errors are clustered at the TL2 regional level. While we primarily focus on respondents who "mainly" work from home, we also run additional tests where the dependent variable indicates those "sometimes" working remotely. The outputs are reported Appendix Table F.3. We find that the results are qualitatively consistent with our baseline estimates but, quantitatively, the coefficients of most variables are smaller in magnitude. We would expect this, since those "sometimes" working from home may be more like those "never" working from home, who are the reference category.

The pandemic may have caused workers able to work remotely to relocate from cities to less densely-populated areas (cf. Ramani & Bloom, 2021, and Althoff et al., 2022, for an analysis of the US context). One concern when estimating Model 1 is that being able to work remotely may influence the decision of respondents to move out of cities, therefore leading to reverse causality when estimating the coefficients γ_1.[28] Although examining the real-time inflow/outflow of workers within/across TL2 regions is out of the scope of this paper, the EU-LFS data allows to preliminarily identify whether there is a structural change in the composition of the workforce in/out of cities. A statistically significant decrease of one category of respondents (e.g., professionals) in cities, mirrored by an equal increase in less dense/more rural settings would hint at a systematic relocation of such type of respondents. To this aim, the analysis compares

[27] It is important to stress that the risk is minimised but not ruled out, e.g., if the role of potentially omitted regional/local factors changed over time.

[28] At a larger scale, one may be equally concerned about the movement of workers *between* regions, also leading to endogeneity in the estimates of the regional coefficients γ_2.

the regional demographic structure across cities, towns and semi-dense areas, and rural locations since the onset of the pandemic.

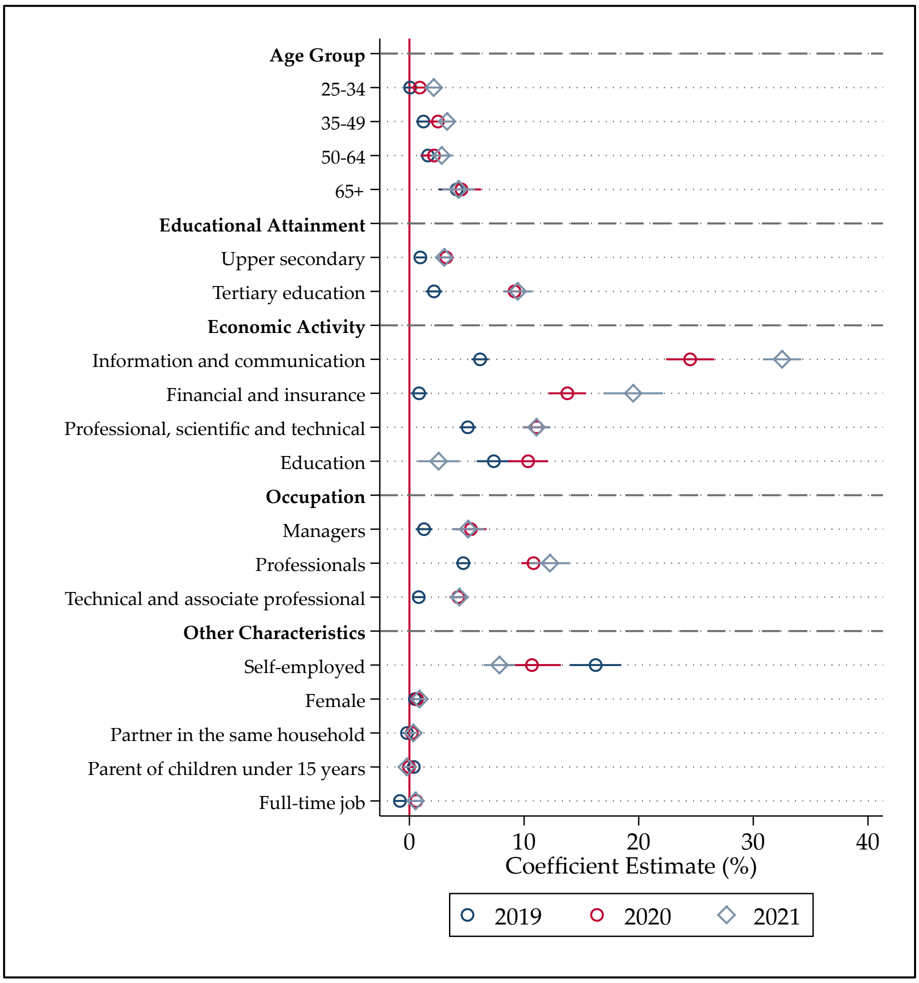
For each of the individual variables included in the vector $PerChar'$, Appendix Table E.1 reports the differences in means between 2021 and 2019 across the different degrees of urbanisation. The appendix also tests if any potential difference in means is statistically significant. While future work will need to explore this important point in more details, the preliminary results suggest that most shares did not significantly change during the pandemic. In other words, even if recent research has explored incipient changes in locational trends in and out of cities (Burgalassi, Jansen, forthcoming), our data show that these changes have not yet occurred in big enough numbers to make reverse causality a main source of concern in our analysis.

Regression results

Figure 5 reports the regression coefficients and their 95% confidence intervals from a parsimonious specification of Equation 1, where the degree of urbanisation and the two regional indicators are not included, i.e., exclusively controlling for the composition hypothesis. The figure presents separate estimates for 2019, 2020, and 2021 (it is important to remember that the data is a repeated cross-section, and it is hence not possible to build a panel).

For reasons of space, the detailed regression coefficient estimates are reported in Appendix Table F.1. Since the dependent variable is binary, the appendix also reports a set of results estimating Equation (1) with a Logit model instead of a linear one. The non-linear results are broadly in line with the OLS outputs, which we prefer for easier readability.

Figure 5. Who was more likely to work remotely during the pandemic?



Note: The figure plots the regression coefficients and 95% confidence intervals estimated from a parsimonious specification of Equation (1). All regressions control for country-by-month and region-fixed effects. Robust standard errors are clustered at the TL2 level. The detailed coefficient estimates and robust standard errors underlying the figure are reported in Column (1) and (5) of Appendix Table F.1.
Source: own elaboration on data from the European Union Labour Force Survey (EU-LFS).

The findings can be summarised as follows. First, respondents belonging to older age groups are significantly more likely to work remotely.[29] The highest WFH incidence is among workers aged 65 and over, whose coefficient is more than double of the ones for respondents aged 35-49 or 50-64, even after accounting for differences in education attainment, sectors, and occupations.[30] The age group coefficients are similar across years, suggesting that the higher likelihood of older respondents to work remotely is not linked to the higher health risks associated to COVID-19.

---

[29] Urban respondents in the groups of 25-34 years old and 35-49 years old are more likely to work remotely than their rural counterparts during the pandemic, while the groups of 50-64 years old and 65+ years old do not tend to experience such urban-rural divide (see appendix Table F.2).

[30] According to own elaboration on data from the EU-LFS, the shares of people over 65 years old employed are 17.3% (2019), 17.5% (2020), and 18.0% (2021).

The association between older age and remote work may be explained by respondents still in work but already beyond retirement age, who may be more likely to opt for more flexible forms of work.

Second, as expected, the sectors of employment matters. Accounting for differences in other individual characteristics, remote work was higher among respondents involved in information and communication, finance and insurance, professional, scientific, technical, and education sectors. Similarly, all things equal, managers, professionals, technical and associate professionals were more likely to work remotely. We also observe significant urban-rural gaps in remote work within these occupations during the pandemic (see Appendix Table F.4). Holding the same occupations constant, city workers had higher chance to work remotely than rural workers. While it's beyond the scope of our paper to identify why, two possible explanations are: (1) cities may offer contextual factors which may be more favorable to remote workers; (2) similar occupations may involve different tasks in urban and rural areas. For instance, urban managers may be more likely to be involved in sectors more amenable to remote work than rural managers. The heatmaps presented in Appendix Figure A.6 indeed provide strong evidence of differences in remote work potential within similar occupations.[31] Relatedly, even holding age, sectors and occupations constant, tertiary education remains a strong and significant predictor of remote work (confirming the findings of Adams-Prassl et al., 2022; OECD, 2021a, 2021c).

Third, self-employed respondents were more likely to work remotely than employees before and during the pandemic, but the difference shrunk since 2019. One plausible explanation is that self-employed may had already switched towards flexible and more efficient forms of work while, by contrast, before the COVID-19 shock, employers were less favourable to allow employees to work outside of the office. The pandemic may have hence altered employers to alter pre-existing inertia, leading to a more dramatic shift in working patterns. By contrast, full-time vs part-time status is weakly correlated to remote work patterns, both before and during the pandemic.

Finally, and unexpectedly, specific individual characteristics such as gender, relationship status, and being a parent of children under 15 are virtually uncorrelated with the likelihood of working remotely. Results not presented but available on request suggest that in 2020 and 2021 the coefficient for identifying as a female was positive and significant when all other regressors are excluded. Its magnitude remains however modest, and comparatively smaller than factors such as tertiary education, age, employment status, or economic activity/occupation. This finding is in line with the pre-COVID-19 results by Sostero et al. (2020), who have shown how the incidence

31 While exploring other kinds of heterogeneity is out of the scope of this paper, we acknowledge that it would be an interesting avenue for future research. We thank one anonymous referee for raising this point.

of remote work by gender was similar across the EU, and by Sanchez et al. (2020), who argue that gender has overall a limited power in explaining teleworkability around the world.[32]

Figure 6 then reports the results from estimating a full specification of Equation (1), that is, controlling for the city dummy and the two regional regressors. The coefficients for all the other individual regressors remain nearly unchanged compared to Figure 5, either before or during the pandemic. Controlling for the full set of covariates, the coefficient for $City_{ir}$ is small. This suggests that the urban-rural gap in remote work uptake highlighted in the exploratory analysis is mostly explained by the other regressors. The final part of the section will assess in more depth such a hypothesis.

The coefficient for regional excess mortality, a proxy for the severity of the pandemic, is large, positive and significant in 2020 (even after controlling for individual characteristics). It however reduces in magnitude and significance in 2021 suggesting that, after the initial shock, the decision of respondents to work remotely has been linked to other factors.

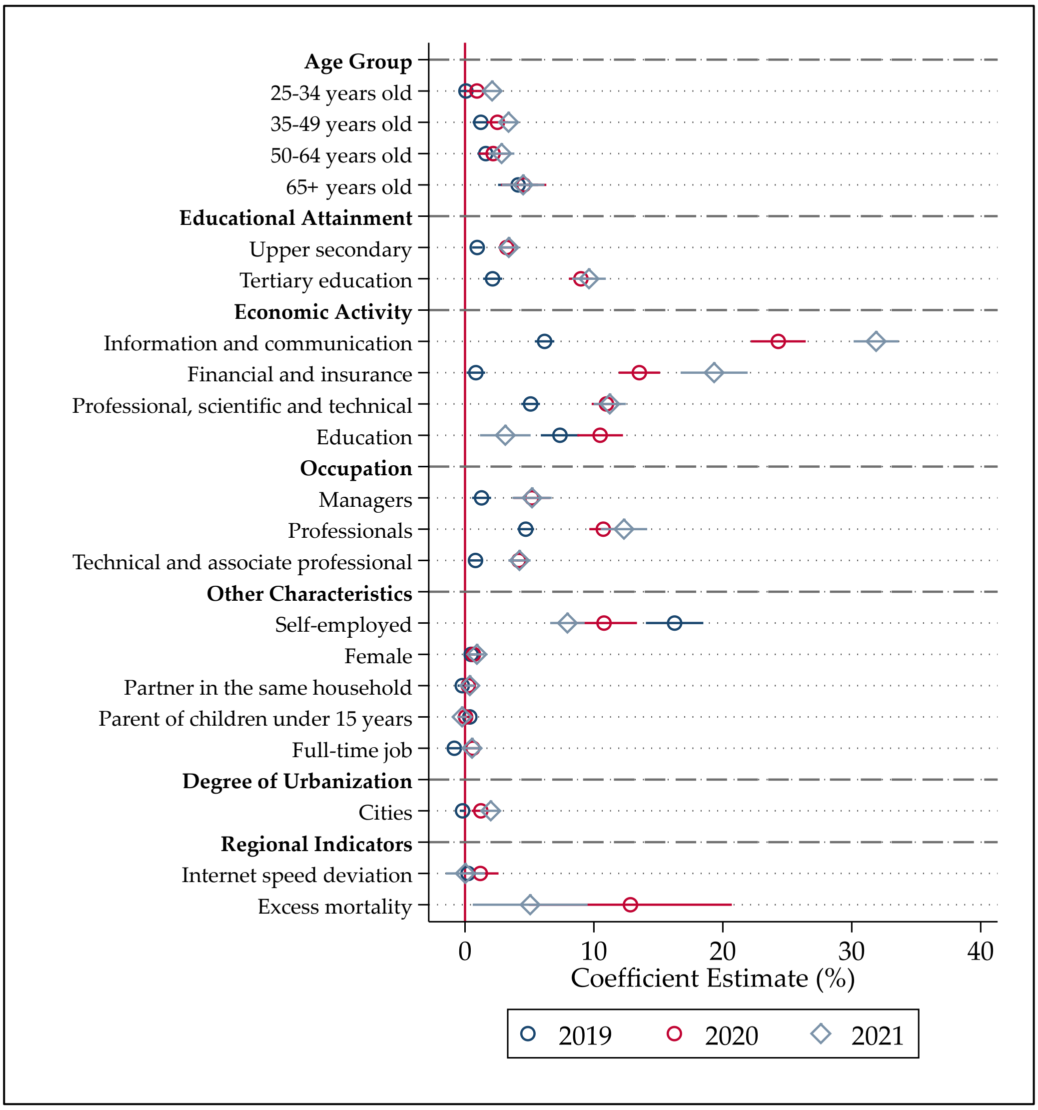
Similarly, the coefficient for the internet speed deviation is close to zero in 2019, it then become is positive and significant in 2020, to reduce again in magnitude and significance in 2021.[33] This may suggest that – pre-pandemic – the choice to work remotely was primarily linked to other factors. Internet speed deviation becomes a significant predictor during the first phase of the pandemic and is comparable to the magnitude obtained for respondents aged 65+, or around half of that for tertiary education. Taken together, these findings may suggest that while internet speed is a precondition, its presence *per se* is not a main driver of remote work.

One may be concerned that the limited explanatory power of the territorial variables may be caused by the inclusion of regional fixed effects, which absorb part of the between-regional variation. As a robustness, we re-run a battery of specifications excluding the regional FEs, as well as dropping the country-by-month FEs. Results, presented in Appendix Table F.7, suggest that this is not the case, as coefficients are overall very similar to when including all the FEs.

[32] Appendix Table F.5 suggests that female workers in the age group of 35-49 were more likely to work remotely than their male counterpart. However, we find that while female workers who hold parent status for children under 15 years old were more likely to work remotely prior to the pandemic, no such difference was observed during the pan-demic (see Appendix Table F.6)

[33] Internet speed in 2021 remains insignificant when excluding all other regressors, or when adopting alternative measures such as average speed rather than regional deviation from the national average.

Figure 6. Who was more likely to work remotely and where?

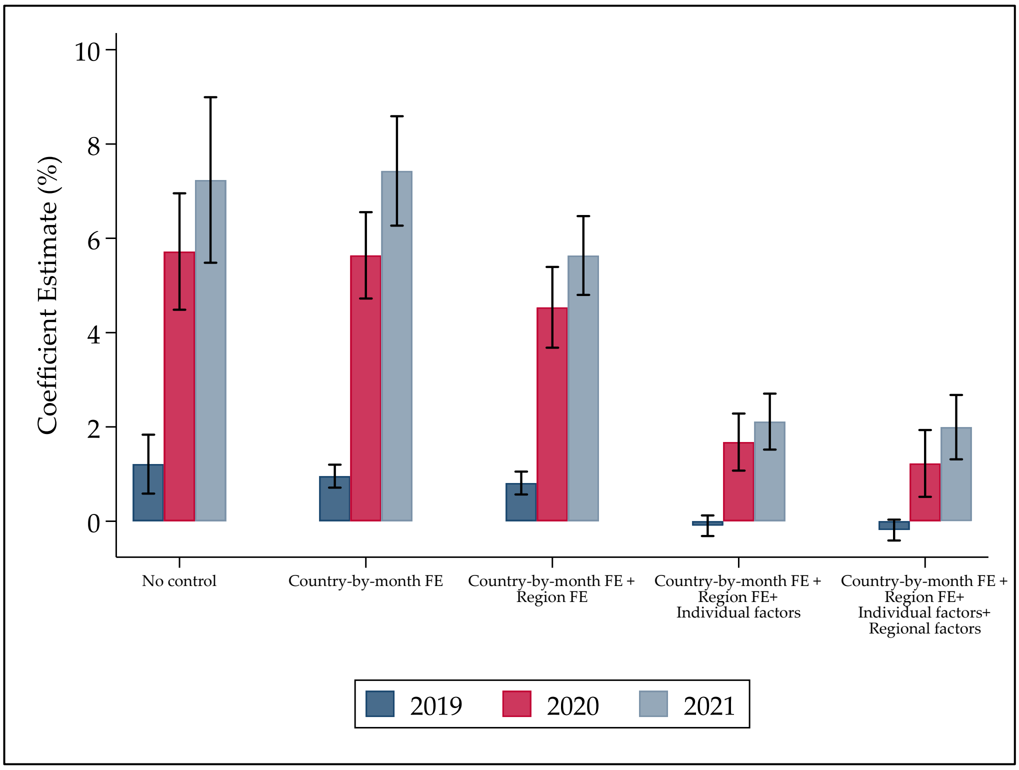


Note: This figure plots coefficient estimates and 95% confidence intervals on various individual and regional factors underlying remote work uptake. All regressions control for country-by-month and region-fixed effects. Robust standard errors are clustered at the TL2 level. Coefficient estimates and robust standard errors are also reported in Column (2) and (6) of Appendix Table F.1.
Source: own elaboration on data from the European Union Labour Force Survey (EU-LFS), OECD.

What explains the gap between cities and other areas?

The descriptive analysis presented in the fourth section showed that cities experienced a higher increase in the share of respondents working remotely. And, yet, in the regression results just presented the coefficient for the city dummy was small and almost insignificant. The current section examines why this might be the case. To this aim, it changes the order in which regressors are added in Equation (1) with the goal of identifying which specific set of factors mediates the correlation between working remotely and the city dummy.

Figure 7. Remote work uptake gaps between cities and other areas (semi-dense and rural)



Note: This figure plots the gap in remote work uptake between cities and other areas (towns and semi-dense areas, and rural areas are combined). The plots show coefficients for 2019, 2020 and 2021 separately, while also reporting 95% confidence intervals. The gaps are estimated by regressing the individual remote work status dummy on a dummy indicating if the respondent lives in an urban area. The figure presents results for five model specifications. Each of the five specifications, corresponding to the sets of vertical columns, respectively includes different sets of covariates as follows: (1) no control; (2) only control for country-by-month fixed effects; (3) control for both country-by-month and region fixed effects; (4) control for country-by-month and region fixed effects, and individual factors; (5) control for country-by-month and region fixed effects, individual and regional factors. For all regressions, robust standard errors are clustered at the TL2 level.
Source: own elaboration on data from the European Union Labour Force Survey (EU-LFS), OECD.

We test five model specifications. Each of them regresses $RemoteWork_{ir}$ on $City_{ir}$, while sequentially including the other regressors. The analysis aims to examine what set of variables "absorbs", i.e., helps explain, the gap in remote work uptake between cities and other areas. The five specifications are defined as follows: (1) no controls (Model 1); (2) controlling for country-by-month fixed-effects (Model 2); (3) controlling for both country-by-month and region FEs (Model 3); (4) controlling for country-by-month and region FEs, as well as for individual regressors (Model 4); (5) controlling for country-by-month and region FEs, individual, and regional factors (Model 5).

Figure 7 presents the results. The largest increase in the models' explanatory power occurs when including the individual regressors. The country-by-month FEs have virtually no effect. Including the regional FEs influences the magnitude of the city dummy, but not substantially. By contrast, the size of the city dummy shrinks substantially after controlling for individual factors in Model 4. Appendix Table G.1 reports the adjusted R^2s of the regressions underlying the results presented in Figure 7.

An important caveat of the previous exercise is that adding regressors sequentially may be misleading if these explanatory variables are correlated among each other. To ensure that the above conclusions do not suffer from such a bias, the analysis follows the decomposition procedure proposed by Gelbach (2016), a method which is insensitive to the order in which regressors are included. The method implies estimating a baseline model with only the main regressor of interest (here the $City_{ir}$ dummy, more generally denoted 'X_1') and, subsequently, estimating a full model where all other covariates (generally denoted 'X_2') are included. The conditional decomposition relies on the least-square identity that links the estimates of the base and full specification coefficients on the main regressor of interest (X_1) via the following omitted variable bias formula:

$$\hat{\beta}_1^{base} = \hat{\beta}_1^{full} + (X_1'X_1)^{-1} X_1'X_2\hat{\beta}_2^{\,1}, \qquad (2)$$

As the decomposition is based on the parameter estimates computed from the full specification, it is order-invariant (Gelbach, 2016).[34]The results suggest that the gap in remote work uptake between cities and other areas is primarily explained by composition effects, i.e., by the concentration in cities of workers with individual characteristics more likely associated with remote work. Table 1 presents the results of the decomposition procedure. The method implies estimating a baseline model with only the main regressor of interest (the $City_{ir}$ dummy) and, subsequently, estimating a full model where all other covariates are included. The estimates for the city dummy are reported in columns (1) and (2). Column (3) shows the difference between the first two columns. Finally, column (4) calculates the extent to which the individual-level set of regressors, as opposed to the regional ones, help explaining the difference of column (3). The table suggests that in 2019, the share of remote workers in cities was 0.84 percentage points higher than in other areas, or -0.19 points lower when controlling for individual and regional factors. In 2020, then, the share of workers working remotely in cities was 4.75 percentage points higher than in other areas. This gap shrinks to 1.23 points when controlling for all the covariates. In 2021, the urban-rural gap in remote work uptake is 5.54 percentage points, or 1.99 percentage points when controlling for all the covariates. (These coefficients correspond to those reported in the third and fifth columns of Figure 7.)

[34] The method builds on the Kitagawa-Oaxaca-Blinder decomposition. See Gelbach (2016) for more details.

Table 1. The role of individual and regional factors as driver of remote work gap between cities and other areas

	Specification		Difference	% Share of column
	Base (1)	Full (2)	between the two specifications (3)	3 explained by each set of factors (4)
Panel A: 2019				
City dummy (i.e., gap between cities and other areas, % points)	0.844*** (0.130)	-0.189* (0.113)	1.033*** (0.114)	
Covariates:				
Individual factors	NO	YES		91.4%
Regional factors	NO	YES		8.6%
Panel B: 2020				
City dummy (i.e., gap between cities and other areas, % points)	4.751*** (0.462)	1.226*** (0.359)	3.525*** (0.436)	
Covariates:				
Individual factors	NO	YES		87.6%
Regional factors	NO	YES		12.4%
Panel C: 2021				
City dummy (i.e., gap between cities and other areas, % points)	5.535*** (0.438)	1.994*** (0.346)	3.542*** (0.311)	
Covariates:				
Individual factors	NO	YES		99.7%
Regional factors	NO	YES		0.3%

Note: This table reports the gap in remote work uptake between cities and other areas and measures the extent to which this gap that can be explained by individual as opposed to regional sets of regressors. Standard errors are in parentheses. *: Significant at 10%; **: 5%; ***: 1%.
Source: own elaboration on data from the European Union Labour Force Survey (EU-LFS), OECD.

Importantly, in 2019, individual factors explained around 91.4% of the difference reported in column 3. By contrast, regional-level regressors account for only 8.6% of the difference reported in column 3. In the wake of the pandemic, while the influence of regional factors marginally increased, individual factors still accounted for 87.6% of the gap between urban and other areas. In 2021, the contribution of individual factors even reaches 99.7%. Together, we conclude that the urban-rural gap in remote work uptake is primarily driven by composition effects.

Conclusion and implications

The COVID-19 pandemic prompted a seismic shift in how work is conducted. Consequently, we have seen an increase in the number of remote workers. Despite this growing phenomenon, is working from home, by which we mean both fully-remote and hybrid jobs, going to significantly alter the economic geography of the global-city system and lead to a ‘big city exodus’ (Nathan, 2023)? Research from the US suggests that this has not, in fact, been the case (Ramani & Bloom, 2021). But what are the trends in Europe?

Contributing the growing body of literature on remote working and its potential spatial effects (inter alia: Althoff et al., 2022, Crescenzi et al., 2022; Fiorentino et al., 2022; Florida et al., 2021; Glaeser, 2022; Nathan, 2023; Nathan & Overman, 2020; Ramani & Bloom, 2021), the paper provides the first systematic exploration of the new geography of remote work that has emerged across 30 European countries, documenting the uneven expansion of work from home across the continent. It then summarises the factors which, according to the literature, are associated with remote work uptake, distinguishing between three groups of drivers, namely compositional (e.g., age, gender and family structure, educational attainments, sector/occupation of work, etc.), contextual (such as internet speed and local severity of the pandemic), and societal (e.g., national lockdown policies). We also exploit a decomposition procedure to assess the relative power of each group in explaining the urban/rural gap in remote work uptake that we observe in the data.

The analysis shows that the spread of remote work has been markedly uneven. Before the pandemic, most areas had similar shares of remote workers. Since 2020, while all European countries have experienced a rise in remote working, its uptake was highly uneven across and within countries. While international differences are closely linked to the stringency of government lockdown policy, countries with strongest pre-pandemic levels also experienced a higher uptake. At the subnational level, remote work uptake was strongest in cities and capital regions.

The results also show that the subnational uneven expansion of WFH across space is primarily explained by composition effects and the uneven distribution of workers and industries more amenable to working remotely. Within each region, age, self-employment status, and higher educational attainments are strong predictors of the individual likelihood of working remotely. Moreover, remote work is closely related to specific service industries such as information and communication technology, finance and insurance, and education. Similarly, respondents occupied as managers, professionals, technical and associate professionals have a higher chance of switching to remote work. Surprisingly, gender, relationship status, and being a parent of children under 15 are not significantly associated with actual remote work uptake.

Regional factors such as internet speed and regional excess mortality are positively associated with the growth of remote working in 2020, but their explanatory power and significance decrease in 2021. Besides, their overall role in explaining the likelihood of working remotely is smaller than the influence of workers' individual attributes. Similarly, the remote work gap between cities and other areas is also primarily driven by composition effects.

While the paper offers novel systematic evidence on the geography of remote work in Europe since the onset of the pandemic, future research may address some of the limitations of the current analysis. Because of data availability the current research is only able to focus on the years of the pandemic. While commentators suggest that remote work is here to stay (Bick et al., 2023), future research should explore whether the spatial patterns observed during the pandemic are indeed long-term or, instead, workers and employers will revert in the medium-term to pre-COVID working habits. Relatedly, the European Labour Force Survey does not offer detailed measures of how much time is spent at home as opposed to the workplace. In this paper, we were unable to measure in a more precise way what “mainly” as opposed to “sometimes” working from home implies. Future work may hence try to address this shortcoming by drawing on alternative data sources. Similarly, future comparative work should explore in more depth how, beyond national lockdown measures, country-specific and regional policies are influencing the spread of new forms of work.

The findings of our study shed light on how the pandemic has influenced the spread of remote work in Europe and how it has impacted cities and regions unevenly. Our research underscores that besides essential factors like reliable internet access, individual characteristics, sectoral, and industry composition play a significant role in the rise of remote work during the pandemic. Understanding this new remote work landscape is crucial for policymakers.

From the standpoint of future trends of regional inequalities and development (cf. Iammarino et al., 2019), then, while remote work may in theory benefit mid-sized towns and peripheral areas, many workers will continue to stay in their regions, especially just outside city centres. Working from home may even favour further agglomeration of economic activities around larger urban areas, especially when workers are asked to go to the office at least a few days ag week. As argued by Bond-Smith and McCann (2022), the fall in commuting frequency associated with WFH may counterintuitively favour larger urban areas where commuting distances are longer.[35]

Considering these trends, some rural areas and towns may succeed in attracting remote workers, especially when they can offer attractive amenities and are relatively close to large cities. More generally, however, local governments should focus on developing suburban areas to accommodate the influx of remote workers and provision of quality public services and amenities. Investment in infrastructure, housing, co-working spaces and community facilities in suburbs can attract professionals and enhance residents' quality of life. However, it's vital to strike a balance, preserving the essence of urban centres. Smart urban planning initiatives like mixed-use zoning and green spaces can make urban living attractive for remote and non-remote workers alike.

Finally, these results revealed challenges related to the ability of some workers to adopt remote working schedules. Recognizing the changing nature of work, and the preference of most workers for more workplace flexibility (Aksoy et al., 2022), policymakers should invest in

[35] As the two authors argue, rather than allowing work from anywhere, the remote work revolution generates greater forces to live within a commutable distance of ever-larger cities. This is because remote (and flexible) work reduces the cost of commuting while, at the same time, cities continue to offer a series of agglomeration economies and amenities often not available outside of urban areas.

upskilling and reskilling programs tailored to remote-friendly industries. By recognizing the role of composition factors and addressing barriers to remote work adoption, policymakers can create more inclusive and remote-friendly work environments, ensuring that the potential benefits associated with remote work are accessible to all, regardless of where they live.

Data statement

The codes used for this research are available by the authors on request. The dataset, by contrast, cannot be shared since the EU-LFS has restricted access. Interested researchers need to apply to Eurostat for microdata access.[36]

[36] https://ec.europa.eu/eurostat/web/microdata/european-union-labour-force-survey, accessed in February 2023.

References

Adams-Prassl, A., Boneva, T., Golin, M. & Rauh, C. (2022), 'Work That Can Be Done from Home: Evidence on Variation within and across Occupations and Industries', Labour Economics 74, 102083.

Ahrend, R., et al. (2023), "Expanding the doughnut? How the geography of housing demand has changed since the rise of remote work with COVID-19", OECD Regional Development Papers, No. 54, OECD Publishing, Paris.

Aksoy, C. G., Barrero J. M., Bloom N., Davis S.J., Dolls M. & Zarate P. (2022), 'Working from home around the world', National Bureau of Economic Research; 2022 Sep 12.

Alon, T., Doepke, M., Olmstead-Rumsey, J. & Tertilt, M. (2020), 'The Impact of COVID-19 on Gender Equality', NBER Working Paper.

Althoff, L., Eckert, F., Ganapati, S. & Walsh, C. (2022), 'The Geography of Remote Work', Regional Science and Urban Economics 93, 103770.

Ascani, A., Faggian, A., Montresor, S. (2020), 'The geography of COVID-19 and the structure of local economies: The case of Italy', Journal of Regional Science, 61(2), 407-441.

Barbieri, T., Basso, G., Scicchitano, S. (2022), 'Italian workers at risk during the COVID-19 epidemic.' Italian Economic Journal, 8(1):175–195.

Barrero, J.M., Bloom, N., Davis, S.J. (2021), 'Why working from home will stick', NBER Working Paper nr. 28731, National Bureau of Economic Research, Cambridge MA.

Bick, A., Blandin, A., Mertens, K. (2023), 'Work from home before and after the COVID-19 outbreak', American Economic Journal: Macroeconomics 15(4), 1-39.

Bond-Smith, S., McCann, P. (2022), 'The work-from-home revolution and the performance of cities', The Productivity Institute Working Paper Series, n. 26, September 2022.

Braesemann, F., Lehdonvirta, V. & Kässi, O. (2022), 'ICTs and the Urban-Rural Divide: Can Online Labour Platforms Bridge the Gap?', Information, Communication & Society 25(1), 34–54.

Brail, S., Kleinman, M. (2022), 'Impacts and implications for the post-COVID city: the case of Toronto', Cambridge Journal of Regions, Economy and Society, 15(3), 495-513.

Brucks, M.S., Levav, J. (2022), 'Virtual communication curbs creative idea generation', Nature, 605(7908), 108-112.

Burgalassi, D., Jansen, T. (forthcoming), 'Remote work and locational trends: towards a new spatial equilibrium in the post COVID-19 system of cities?', *OECD Regional Development Working Papers.*

Corradini, C., Matheson, J., Vanino, E. (2022), 'How important s neighbourhood labour structure in the spread of COVID-19? Within-city evidence from England', Sheffield Economic Research Paper Series, 2022011, University of Sheffield.

Crescenzi, R., Giua, M., Rigo, D. (2022), 'How many jobs can be done at home? Not as many as you think', LSE Geography and Environment Discussion Paper Series, n. 37 November 2022.

Cuerdo-Vilches, T., Navas-Martín, M. Á. & Oteiza, I. (2021), 'Working from Home: Is Our Housing Ready?', International Journal of Environmental Research and Public Health 18(14), 7329.

De Fraia, G., Matheson, J., Rockey, J. (2021), 'Zoomshock: The geography and local labour market consequences of working from home' COVID Economics 64, CEPR Press, London, 1-41.

Delventhal, M., Kwon, E., Parkhomenko, A. (2022), 'JUE insights: How do cities change when we work from home', Journal of Urban Economics, 127, 103331.

De Vos, D., Lindgren, U., van Ham, M., Meijers, E. (2020), 'Does broadband internet allow cities to borrow size? Evidence from the Swedish labour market', Regional Studies, 54(9), 1175-1186.

Diaz-Ramirez, M., Veneri, P., Lembcke A.C. (2022), 'Where did it hit harder? Understanding the geography of excess mortality during the COVID-19 pandemic', Journal of Regional Science 62(3), 889-908.

Dijkstra, L., Florczyk, A. J., Freire, S., Kemper, T., Melchiorri, M., Pesaresi, M. & Schiavina, M. (2021), 'Applying the Degree of Urbanisation to the Globe: A New Harmonised Definition Reveals a Different Picture of Global Urbanisation', Journal of Urban Economics 125, 103312.

Dingel, J. I. & Neiman, B. (2020), 'How Many Jobs Can be Done at Home?', Journal of Public Economics 189, 104235.

Eurofound (2020), Living, Working and COVID-19, Technical report, Publications Office of the European Union, Luxembourg.

European Commission (2021), 'Harnessing Innovation to Unlock the Potential of Rural and Remote Areas'. URL: https://digital-strategy.ec.europa.eu/en/news/harnessing-innovation-unlock- potential-rural-and-remote-areas.

Florida, R., Storper, M. & Rodríguez-Pose, A. (2023), 'Critical commentary: Cities in a Post-COVID World', Urban Studies, 60(8), 1509-1531.

Fiorentino, S., Livingstone, N., McAllister, P., Cooke, H. (2022), 'The future of the corporate office? Emerging trends in the post-COVID city', Cambridge Journal of Regions, Economy and Society 15, 597-614.

Gelbach, J. B. (2016), 'When Do Covariates Matter? And Which Ones, and How Much?', Journal of Labor Economics 34(2), 509–543.

Glaeser, E. L. (2022), 'Urban Resilience', Urban Studies 59(1), 3–35.

Gokan, T., Kichko, S., Matheson, J.A., Thisse, J.F. (2022), 'How the rise of teleworking will reshape labor markets and cities', CESifo Working Paper no 9952, September.

Gottlieb, C., Grobovšek, J., Poschke, M. & Saltiel, F. (2021), 'Working from Home in Developing Countries', European Economic Review 133, 103679.

Grabner, S. M. & Tsvetkova, A. (2022), 'Urban Labour Market Resilience during the COVID-19 Pandemic: What Is the Promise of Teleworking?', Regional Studies pp. 1–16.

Hale, T., Anania, J., Angrist, N., Boby, T., Cameron-Blake, E., Folco, M. D., Ellen, L., Goldszmidt, R., Hallas, L., Kira, B., Luciano, M., Majumdar, S., Nagesh, R., Petherick, A., Phillips, T., Tatlow, H., Webster, S., Wood, A. & Zhang, Y. (2021), 'Variation in Government Responses to COVID-19 (Version 12.0)', Blavatnik School of Government Working Paper.

Huggins, R., Thompson, P. (2022), 'Cities, innovation and entrepreneurial ecosystems: assessing the impact of the COVID-19 pandemic', Cambridge Journal of Regions, Economy and Society, 15(3), 635-661.

ILO (2020), COVID-19: Guidance for Labour Statistics Data Collection: Defining and Measuring Remote Work, Telework, Work at Home and Home-Based Work, Technical report, International Labour Organization.

Kyriakopoulou, E., Picard, P.M. (2023), 'The Zoom city: working from home, urban productivity and land use', Journal of Economic Geography, AoP, https://doi.org/10.1093/jeg/lbad025.

Legeby, A., Koch, D., Duarte, F., Heine, C., Benson, T., Fugiglando, U., Ratti, C. (2023), 'New urban habits in Stockholm following COVID-19', Urban Studies 60(8), 1448-64.

Mariotti, I., (2021), 'Is remote working emptying the city?', Regions, 1-11.

Mariotti, I., Capdevila I., Lange B. (2023), 'Flexible geographies of new working spaces', European Planning Studies, 31(3), 433-444.

Mariotti, I., Di Marino, M., Bednar, P. (2023, eds.), The COVID-19 pandemic and the future of working spaces. London: Routledge.

Nathan, M. (2023), 'Critical commentary: The city and the virus', Urban Studies, 60(8), 1346-1364.

Nathan, M. & Overman, H. (2020), 'Will Coronavirus Cause a Big City Exodus?', Environment and Planning B 47(9), 1537–1542.

OECD (2020a), Capacity for Remote Working Can Affect Lockdown Costs Differently across Places. OECD Policy Responses to Coronavirus (COVID19), Technical report, OECD Publishing, Paris.

OECD (2020b), Regions and Cities at a Glance 2020, Technical report, OECD Publishing, Paris.

OECD (2021a), Implications of Remote Working Adoption on Place Based Policies: A Focus on G7 Countries, Technical report, OECD Publishing, Paris.

OECD (2021b), Teleworking in the COVID-19 Pandemic: Trends and Prospects, Technical report, OECD Publishing, Paris.

OECD (2021c), The Future of Remote Work: Opportunities and Policy Options for Trentino, Technical report, OECD Publishing, Paris.

OECD (2022), OECD Regions and Cities at a Glance 2022, OECD Publishing, Paris.

Ramani, A. & Bloom, N. (2021), 'The Donut Effect of COVID-19 on Cities', NBER Working Paper 28876.

Ramírez, M. D., Veneri, P. & Lembcke, A. C. (2022), 'Where Did It Hit Harder? Understanding the Geography of Excess Mortality during the COVID19 Pandemic', Journal of Regional Science 62(3), 889–908.

Sanchez, D. G., Parra, N. G., Ozden, C., Rijkers, B., Viollaz, M. & Winkler, H. (2021), 'Who on Earth Can Work from Home?', The World Bank Research Observer 36(1), 67–100.

Sostero, M., Milasi, S., Hurley, J., Fernández-Macías, E. & Bisello, M. (2020), 'Teleworkability and the COVID-19 Crisis: A New Digital Divide?', JRC Working Paper Series on Labour, Education and Technology, nr 2020/05.

Stantcheva, S. (2022), 'Inequalities in the Times of a Pandemic', Economic Policy 37(109), 5–41.

Vilhelmson, B. & Thulin, E. (2001), 'Is Regular Work at Fixed Places Fading Away? The Development of ICT-based and Travel-based Modes of Work in Sweden', Environment and Planning A 33, 1015 – 1029.

Yang, L., Holtz, D., Jaffe, S., Suri, S., Sinha, S., Weston, J., Joyce, C., Shah, N., Sherman, K., Hecht, B. & Teevan, J.

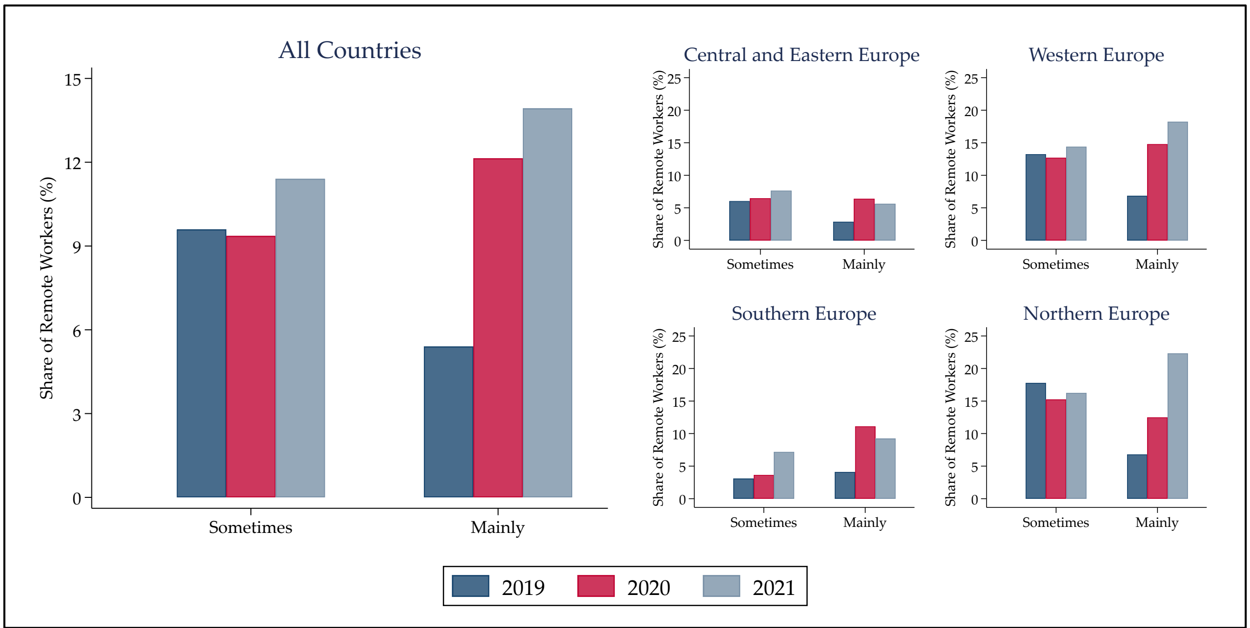
(2022), 'The Effects of Remote Work on Collaboration among Information Workers', Nature Human Behaviour 6(1), 43– 54.

The new geography of remote jobs in Europe

Appendices

Appendix A: Shares of remote workers by country

Figure A.1. Shares of hybrid and remote workers by country macro-groups, 2019 to 2021



Note: This figure plots the shares of remote workers by remote work frequency for 30 European countries in 2019, 2020 and 2021. The left panel shows the weighted average across all countries in the sample (as in Figure 1). The right panels, by contrast, show the weighted averages by subsets of countries. For most countries, the shares of workers who "mainly" worked remotely increased significantly, whereas the shares of workers who "sometimes" worked remotely did not change much.
Source: European Union Labour Force Survey (EU-LFS).

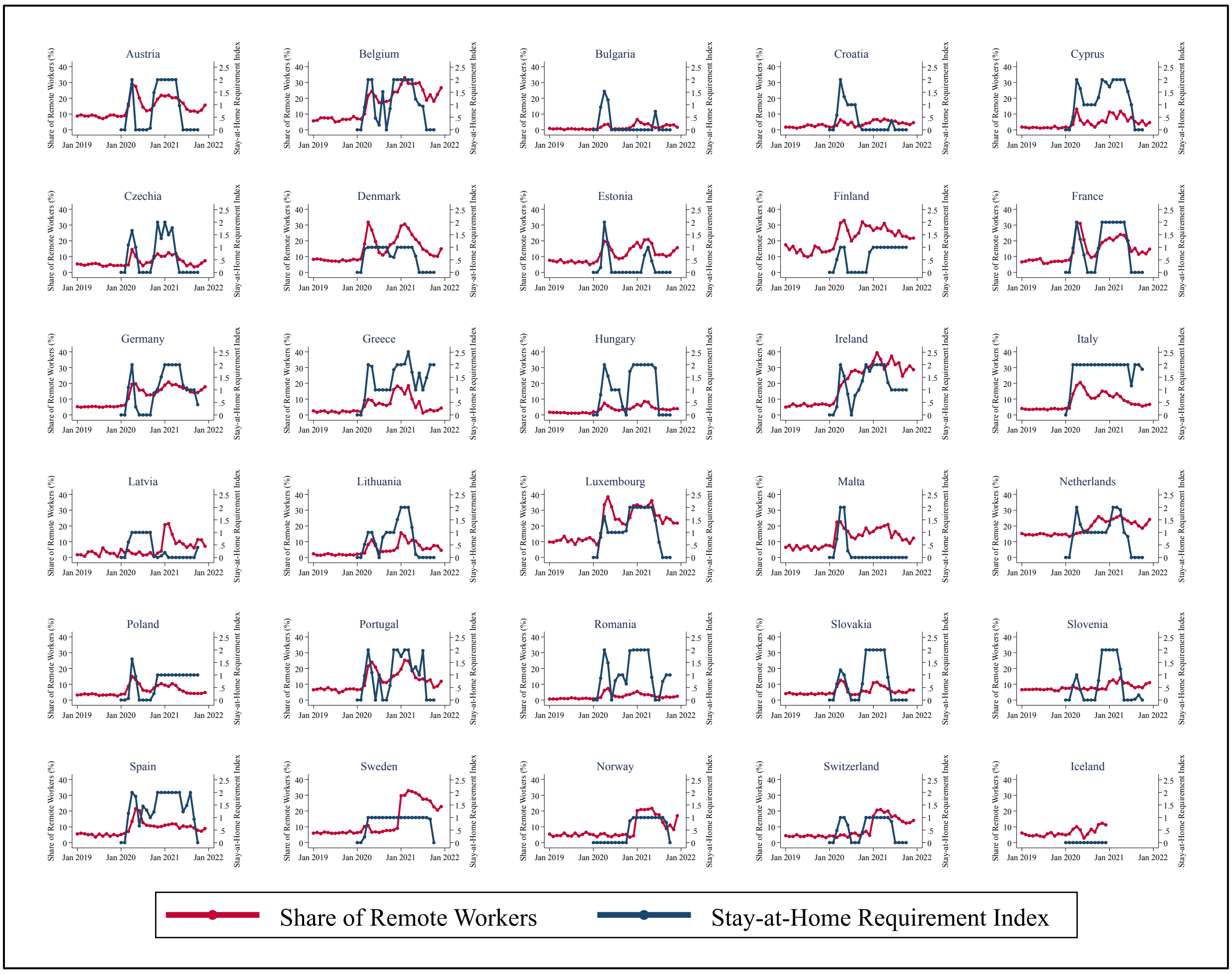
Figure A.2. Shares of hybrid and remote workers, by individual countries, 2019 to 2021

Note: This figure plots shares of remote workers by remote work frequency for 30 European countries in 2019 to 2021. It shows that for most countries, shares of workers who "mainly" worked remotely increased significantly whereas shares of workers who "sometimes" worked remotely varied little.
Source: European Union Labour Force Survey (EU-LFS).

Figure A.3. Monthly shares of remote workers and government policy responses to COVID-19 (overall stringency index), by country, 2019 to 2021

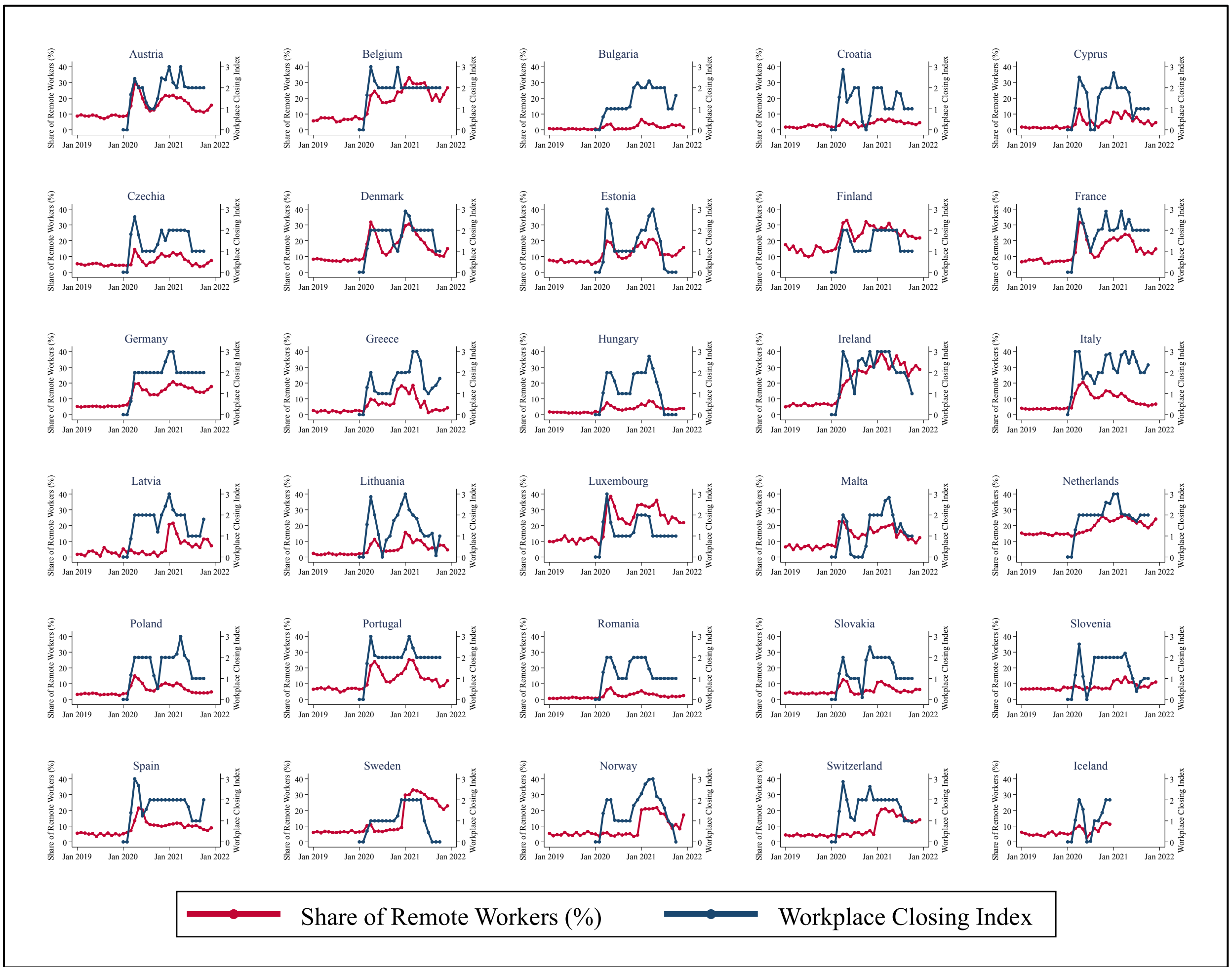
Note: This figure plots the monthly shares of remote workers and an overall index measuring the stringency of government policy responses to COVID-19 for 30 European countries from 2019 to late 2021. It shows that, across most countries, the shares of remote workers closely followed the stringency index.
Source: European Union Labour Force Survey (EU-LFS), stringency index from the Oxford COVID-19 Government Response Tracker (OxCGRT).

Figure A.4. Monthly shares of remote workers and government policy responses to COVID-19 (stay-at-home requirements), by country, 2019 to 2021



Note: This figure plots monthly shares of remote workers and degrees of stringency in government policy responses to COVID-19 (stay-at-home requirements) for 30 European countries from 2019 to late 2021.
Source: European Union Labour Force Survey (EU-LFS), stringency index from the Oxford COVID-19 Government Response Tracker (OxCGRT).

Figure A.5. Monthly shares of remote workers and government policy responses to COVID-19 (workplace closures), by country, 2019 to 2021

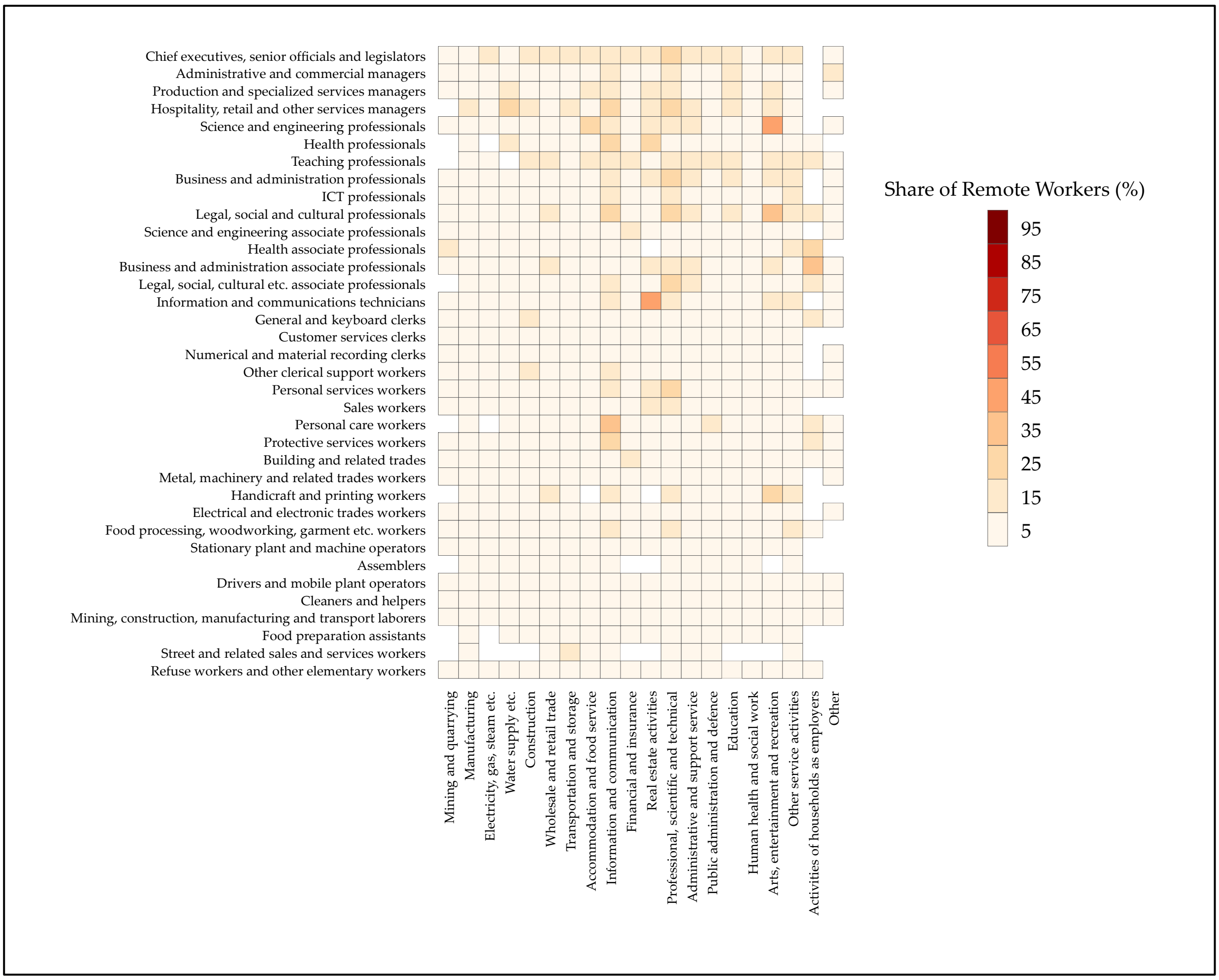


Note: This figure plots monthly shares of remote workers and degrees of stringency in government policy responses to COVID-19 (forced workplace closures) for 30 European countries from 2019 to late 2021.

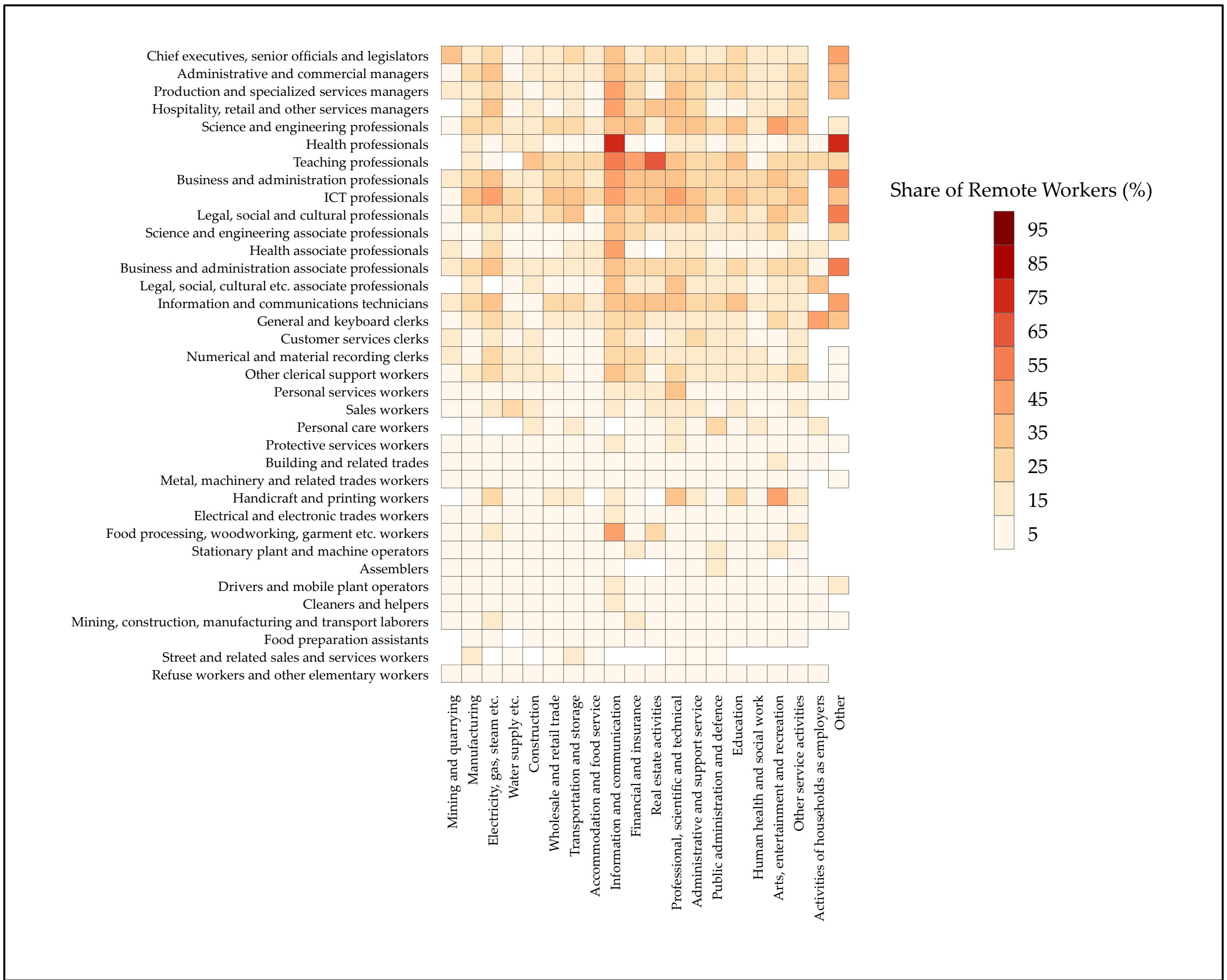
Source: European Union Labour Force Survey (EU-LFS), stringency index from the Oxford COVID-19 Government Response Tracker (OxCGRT).

Figure A.6. Heatmaps of remote work shares for industry-occupation pairs, 2019 to 2021

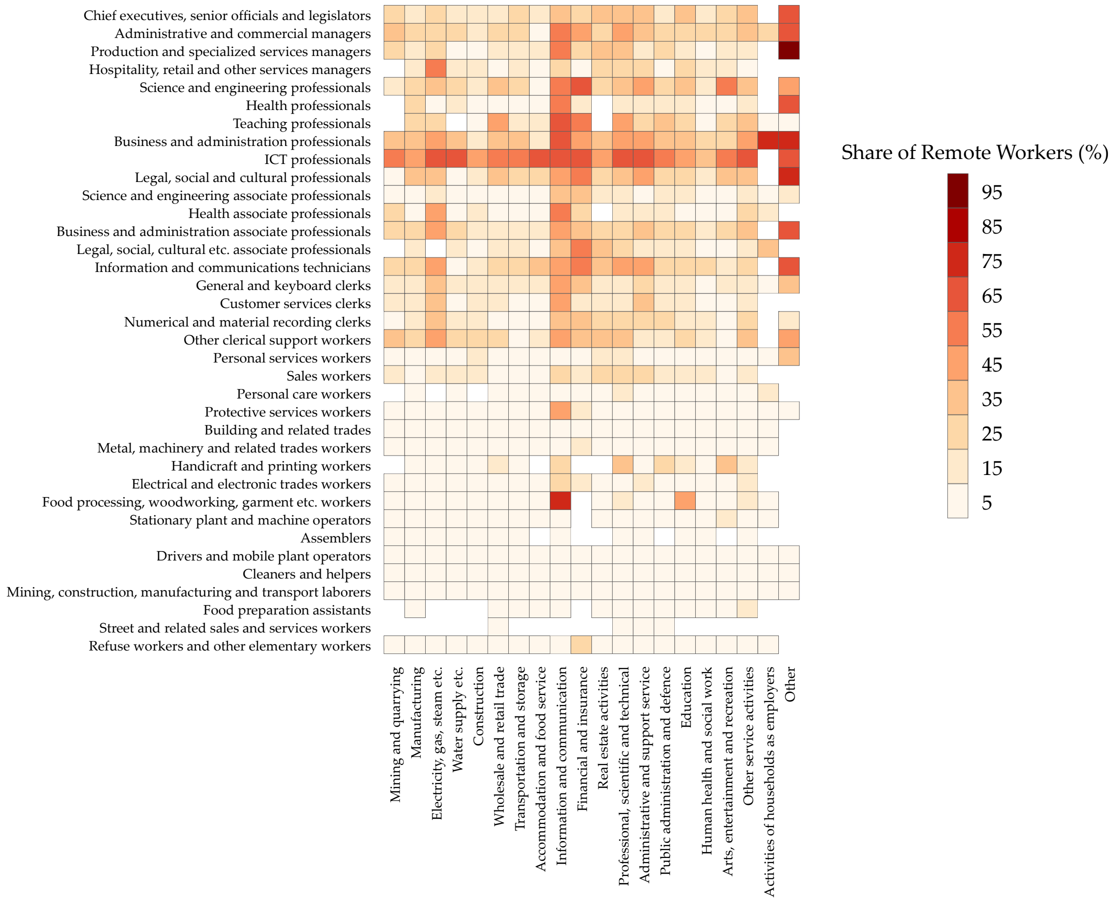
Panel A: 2019



Panel B: 2020

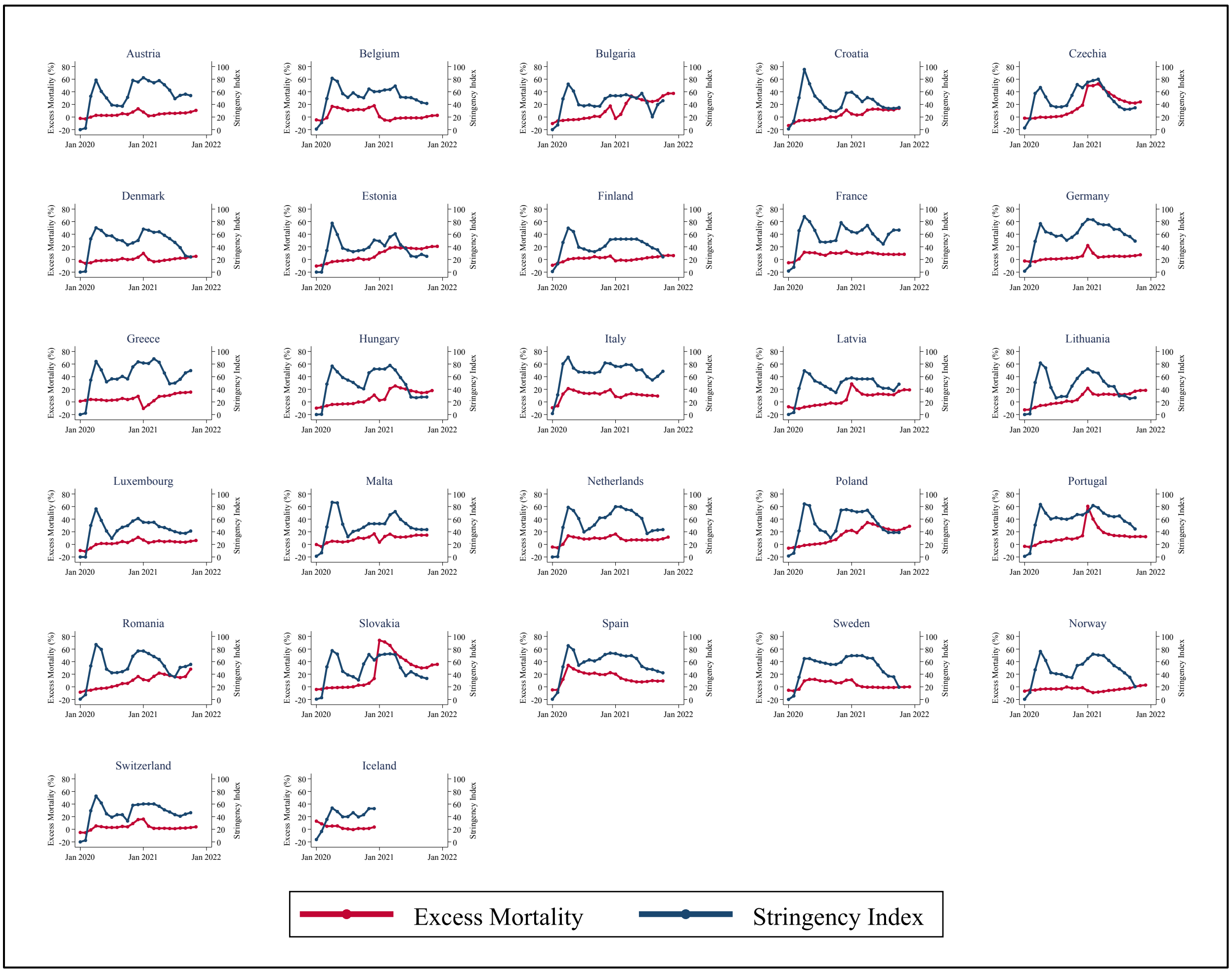

Chief executives, senior officials and legislators
Administrative and commercial managers
Production and specialized services managers
Hospitality, retail and other services managers
Science and engineering professionals
Health professionals
Teaching professionals
Business and administration professionals
ICT professionals
Legal, social and cultural professionals
Science and engineering associate professionals
Health associate professionals
Business and administration associate professionals
Legal, social, cultural etc. associate professionals
Information and communications technicians
General and keyboard clerks
Customer services clerks
Numerical and material recording clerks
Other clerical support workers
Personal services workers
Sales workers
Personal care workers
Protective services workers
Building and related trades
Metal, machinery and related trades workers
Handicraft and printing workers
Electrical and electronic trades workers
Food processing, woodworking, garment etc. workers
Stationary plant and machine operators
Assemblers
Drivers and mobile plant operators
Cleaners and helpers
Mining, construction, manufacturing and transport laborers
Food preparation assistants
Street and related sales and services workers
Refuse workers and other elementary workers
Mining and quarrying
Manufacturing
Electricity, gas, steam etc.
Water supply etc.
Construction
Wholesale and retail trade
Transportation and storage
Accommodation and food service
Information and communication
Financial and insurance
Real estate activities
Professional, scientific and technical
Administrative and support service
Public administration and defence
Education
Human health and social work
Arts, entertainment and recreation
Other service activities
Activities of households as employers
Other
Share of Remote Workers (%)
95
85
75
65
55
45
35
25
15
5

Panel C: 2021



Note: This figure plots the shares of remote workers for each of the 720 industry-occupation pairs (20×36). The pairs whose number of observations is less than 10 are dropped. Panel A shows data for 2019, Panel B for 2020 and Panel C for 2021. Overall, the figure suggests that the shares became more heterogeneous in 2020; the industries such as “information and communication”, “financial and insurance”, “professional, scientific and technical”, and “education” had relatively high remote work uptake and so did the occupations such as managers, professionals, and associate professionals.
Source: European Union Labour Force Survey (EU-LFS).

Figure A.7. Monthly excess mortality and government policy responses to COVID-19 (overall stringency index), by country, 2020 to 2021



Note: This figure plots the excess mortality and an overall index measuring the stringency of government policy responses to COVID-19 for 27 European countries from 2020 to late 2021. We do not have excess mortality data for Cyprus, Ireland, and Slovenia.
Source: Ramírez et al. (2022), stringency index from the Oxford COVID-19 Government Response Tracker (OxCGRT).

Appendix B: The measurement of remote work potential

We follow the approach by Dingel & Neiman (2020) to measure remote work potential. Specifically, the first step is to identify whether an occupation by 6-digit U.S. Standard Occupational Classification (SOC) is amenable to remote work according to the nature of the tasks required.[37] For example, if the use of email for the occupation is infrequent or it requires employees to work outdoors every day, that occupation can be classified as one that is not amenable to remote work. In Dingel & Neiman (2020), they used 9 questions of the Work Context survey and 8 questions of the Generalised Work Activities survey, both in the US O*NET database, to specify conditions determining the feasibility of working remotely for various 6-digit SOC occupations. These conditions are summarised in Table B.1. If any of the conditions are satisfied, they code that occupation as one that cannot be performed at home. Table B.1 also reports the shares of jobs that satisfy the corresponding conditions. As can be seen from the table, the three most frequently satisfied conditions are “majority of time wearing protective or safety equipment” (39%), “majority of time walking or running” (29%), and “performing or working directly with the public” (22%), whereas the two less frequently satisfied conditions are “dealing with violent people at least once a week” (1%) and “repairing and maintaining electronic equipment” (1%). Note that multiple conditions can hold for any single occupation, so the sum of the shares in the table can far exceed the real total share of jobs that cannot be performed entirely at home.

These 6-digit SOC occupations are then mapped to occupations by 2-digit International Standard Classification of Occupations (ISCO) so as to identify the shares of jobs that can be done remotely (remote-workable shares) within each 2-digit ISCO occupation available in the data sets used in this paper.[38] Ideally, the remote-workable share for each 2-digit ISCO can be aggregated as the weighted average of the shares of corresponding 6-digit SOC occupations, with SOCs’ US employment counts as the weights, if each SOC only maps to a unique ISCO. However, since the mapping relationship is many-to-many rather than many-to-one, the preceding approach would allocate disproportionate weights to those SOCs that map to a bulk of ISCOs. To tackle this issue, Dingel & Neiman (2020) propose another weight assignment scheme: when an SOC maps to multiple ISCOs, the weight on the SOC for each ISCO is specified by the SOC's US employment counts multiplying by the employment share of each ISCO among the mapped ISCOs.

This study draws on the data from European Union Labour Force Surveys (2019, 2020, 2021) to measure the remote-workable shares of 2-digit ISCOs. The major advantage of EU-LFS is that it

[37] The version of SOC is the SOC 2010.

[38] The version of ISOC is the ISOC-08.

provides individuals' occupation information at the 3-digit ISCO level across all the countries considered. As such, it is possible to map the 6-digit SOCs to 2-digit ISCOs.

The remote-workable shares for 2-digit ISCOs can be further aggregated into those of 1-digit ISCOs, various regions, and demographic groups. The remote-workable shares for 1-digit ISCOs can be calculated as the weighted average of the remote-workable shares of 2-digit ISCOs, using the 2-digit ISCOs' employment counts as the weights. Similarly, the remote-workable shares for regions (e.g., European TL2 regions) can be obtained by the weighted average of the remote-workable shares of 2-digit ISCOs, using the 2-digit ISCOs' employment counts in the corresponding regions as the weights. Herein, one thing that needs to be emphasised is that the remote-workable shares for each 2-digit ISCO might differ across regions and demographic groups. This is not striking since the employment shares of ISCOs might vary by regions and demographic groups, and therefore, as discussed above, averaging the 6-digit SOCs' remote-workable indicators into remote-workable shares of 2-digit ISCOs for different regions is by no means identical.

Table B.1. Conditions to identify remote-workability of occupations

Question ID	Condition	% of Jobs
Panel A: Work Context Survey		
Q4	Average respondent says they use email less than once per month.	17
Q14	Average respondent says they deal with violent people at least once a week.	1
Q17&Q18	Majority of respondents say they work outdoors every day.	4
Q29	Average respondent says they are exposed to diseases or infection at least once a week.	8
Q33	Average respondent says they are exposed to minor burns, cuts, bites, or stings at least once a week.	2
Q37	Average respondent says they spent majority of time walking or running.	29
Q43&Q44	Average respondent says they spent majority of time wearing common or specialised protective or safety equipment.	39
Panel B: Generalized Work Activities Survey		
Q16A	Performing General Physical Activities is very important.	11
Q17A	Handling and Moving Objects is very important.	9
Q18A	Controlling Machines and Processes [not computers nor vehicles] is very important.	5
Q20A	Operating Vehicles, Mechanized Devices, or Equipment is very important.	6
Q32A	Performing for or Working Directly with the Public is very important.	22
Q22A	Repairing and Maintaining Mechanical Equipment is very important.	2
Q23A	Repairing and Maintaining Electronic Equipment is very important.	1
Q4A	Inspecting Equipment, Structures, or Materials is very important.	11

Note: This table summarises the conditions that are used to identify an occupation's remote-workability and the proportions of jobs that meet the corresponding conditions. Dingel & Neiman (2020) draw on the data from Work Context Survey and Generalized Work Activities Survey in the O*NET database to classify the feasibility of working remotely for various occupations. If any of the conditions above are met, they code that occupation as one that cannot be performed remotely. Note that multiple conditions can hold for any single occupation. The proportions in this table are extracted from 'Jobs' Column in Table B.1 of Dingel & Neiman (2020).
Source: Dingel & Neiman (2020).

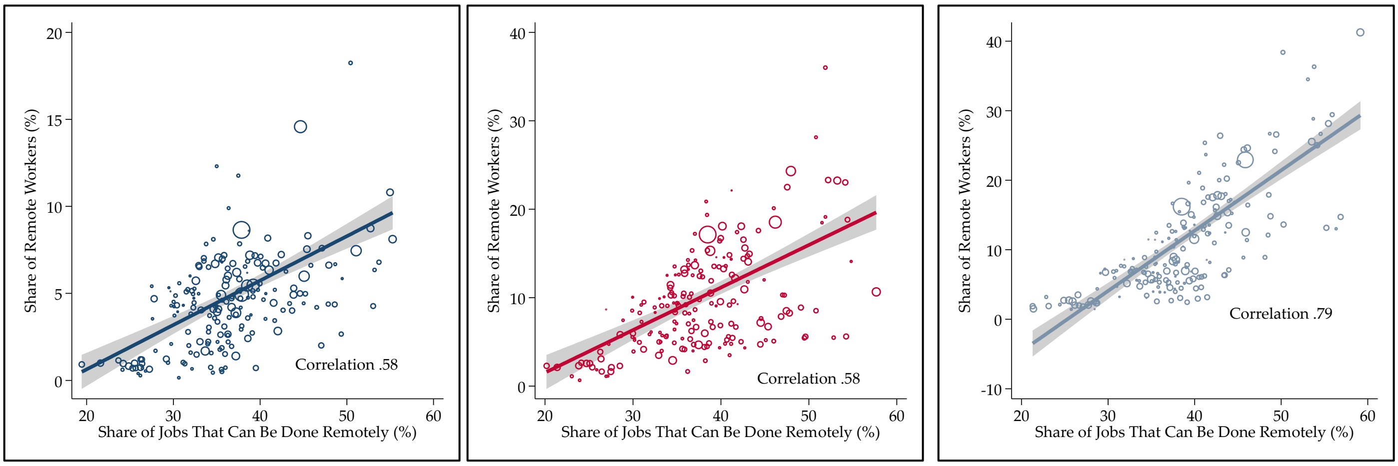
Appendix C: The correlation between potential and actual remote work

Based on annual regional samples, this appendix tests how the measure of *actual* remote work is correlated with the indicator of remote work *potential* developed following the method proposed by Dingel & Neiman (2020) and discussed in Appendix B. Their approach is to identify the shares of jobs that can be done remotely according to the nature of the tasks required. For instance, if the use of email for a job is infrequent, or if it requires employees to work outdoors every day, that job is classified as one that is not amenable to remote work. Using information about how many jobs of each type are currently available at the TL2 regional level, one can calculate a measure of regional, remote work potential.

Figure C.1 plots the bivariate correlation between the regionally aggregate (at TL2 level) measure of remote work update during the pandemic and the measure of remote work potential. The results suggest that regional remote work potential could well forecast actual remote work uptake levels both before and during the pandemic. The correlation coefficients of these two shares were 0.58 in 2019, 0.58 in 2020, and 0.79 in 2021 respectively.

Figure C.1. Actual remote work uptake and remote work potential

Panel A: 2019 Panel B: 2020 Panel C: 2021



Note: This figure plots regional shares of remote workers (actual remote work uptake) against regional shares of jobs that can be done remotely (remote work potential). It shows that regional remote work potential could well forecast actual remote work uptake levels before and during the pandemic. Each bubble denotes a TL2 region, with sizes proportional to regions' numbers of observations. The lines depict the linear relationships (weighted by the number of observations of each region) between the two shares, with 95% confidence intervals shown as the grey shading areas.
Source: European Union Labour Force Survey (EU-LFS).

Appendix D: Descriptive statistics

Table D.1. Descriptive statistics for key individual variables from the EU-LFS

Variable	A: 2019 (Sample Size: 1,592,543)		B: 2020 (Sample Size: 1,211,800)		C: 2021 (Sample Size: 1,105,802)	
	Rel. share (%)	Resp. rate (%)	Rel. share (%)	Resp. rate (%)	Rel. share (%)	Resp. rate (%)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Remote work						
Remote work	5.4	89.5	12.1	97.3	13.9%	96.5%
Panel B: Age group						
17-24 years old	6.6	89.7	6.3	97.6	6.5%	97.0%
25-34 years old	19.1	89.7	18.9	97.6	18.8%	97.0%
35-49 years old	34.6	89.7	34.3	97.6	34.1%	97.0%
50-64 years old	27.9	89.7	28.6	97.6	28.6%	97.0%
65+ years old	11.7	89.7	11.8	97.6	12.0%	97.0%
Panel C: Educational attainment						
Lower secondary	15.8	89.5	15.1	97.5	15.0	96.8
Upper secondary	47.9	89.5	47.0	97.5	46.6	96.8
Tertiary education	36.3	89.5	37.9	97.5	38.4	96.8
Panel D: Economic activity						
Information and communication	3.3	89.7	3.7	97.6	3.7	97.0
Financial and insurance	2.9	89.7	3.0	97.6	3.0	97.0
Professional, scientific and technical	5.9	89.7	6.0	97.6	6.1	97.0
Education	7.8	89.7	7.9	97.6	8.0	97.0
Other	80.2	89.7	79.4	97.6	79.2	97.0
Panel E: Occupation						
Managers	5.6	89.7	5.4	97.6	5.4	97.0
Professionals	20.7	89.7	22.1	97.6	23.0	97.0
Technicians & associate professionals	17.7	89.7	17.2	97.6	16.9	97.0
Other	56.1	89.7	55.2	97.6	54.8	97.0
Panel F: Degree of urbanisation						
Cities	41.2	89.7	41.8	97.6	41.8	97.0
Towns and semi-dense areas	34.0	89.7	34.0	97.6	34.6	97.0
Rural areas	24.8	89.7	24.2	97.6	23.5	97.0
Panel G: Other characteristics						
Self-employee	12.5	89.7	12.5	97.6	12.3	97.0
Female	47.1	89.7	47.0	97.6	47.3	97.0
With partner in the same household	65.5	79.6	65.9	83.7	63.8	85.8
Parent of children under 15	33.8	79.6	33.6	83.7	33.2	85.8
Full-time job	80.1	89.7	80.4	97.6	80.7	96.9

Note: This table presents the average share values and the response rates for each sociodemographic variable included in the analysis. It reports separately values for the 2019, 2020 and 2021 samples. In each panel, the relative shares sum up to 100. Exceptions are Panel A and G, where the table does not show the relative share of workers in the opposite categories. The samples are comprised of all employees and self-employees aged 17 and over (excluding workers in agriculture, forestry and fishing, and armed forces). For simplicity, all other NAE economic activities and ISCO-08 occupations not reported in the table are classified under "other".
Source: European Union Labour Force Survey (EU-LFS).

Table D.2. Descriptive statistics for the regional-level variables

Variable	Mean	Standard Deviation	Number of Regions Matched		
			Total	TL2	TL1
Panel A: 2019					
Excess mortality (%)	NA	NA	NA	NA	NA
Internet speed deviation (%)					
Cities	20.183	2.543			
Towns and semi-dense areas	-5.940	1.698	196	192	4
Rural areas	-30.691	2.203			
Panel B: 2020					
Excess mortality (%)	3.954	0.222	190	186	4
Internet speed deviation (%)					
Cities	22.995	2.762			
Towns and semi-dense areas	-6.738	1.657	200	196	4
Rural areas	-29.653	1.849			
Panel B: 2021					
Excess mortality (%)	12.452	0.279	190	186	4
Internet speed deviation (%)					
Cities	23.017	2.732			
Towns and semi-dense areas	-8.000	1.529	197	193	4
Rural areas	-24.744	1.679			

Note: This table presents key descriptive statistics for the regional-level variables. 'NA' denotes non-available. All averages are weighted by the numbers of observations of regions in EU-LFS. Excess mortality and internet speed deviation (relative to national averages) are matched to EU-LFS at the TL2 level. Exceptions include Austria, Iceland, Netherlands, and Croatia where we match at the TL1 level due to data availability. We do not have excess mortality data for Cyprus and Ireland. Internet speed deviation data are matched to EU-LFS by region by degree of urbanization by year. Excess mortality data are matched to EU-LFS by region by month.
Source: OECD Regional Database and Ramírez et al. (2022).

Appendix E: Potential changes in demographic composition between cities and other areas

Appendix Table E.1 measures whether various demographic indicators changed between 2021 and 2019 across cities, towns and semi-dense areas, and rural areas. The table also reports p-values for t-tests to assess whether any potential difference is statistically significant. The results suggest that most shares did not show significant changes across the pandemic. In other words, there is no evidence of a structural reshuffling of workers across areas at different degrees of urbanisation. Therefore, it can be concluded that reverse causality between place of residence and working remotely should not be a main source of concern in the short period analysed here. A minor exception is the share of professionals, which in 2021 decreases in a statistically significant way across all areas, but comparatively more in urban areas than in rural ones (-2.13% vs -1.12%). Similarly, the share of respondents living with a partner and with children under 15 increases across all areas, but comparatively more in rural settings (+5.04% and +1.59% respectively) than in cities (+3.15% and +0.63% respectively). Yet, the fact that these variables show coefficient with similar signs across locations make us think of small differences in sampling, rather than structural movement of people.

Table E.1. Changes in regional demographic structures between 2021 and 2019, by degrees of urbanisation

Urbanisation	**Cities**		**Towns and semi-dense areas**		**Rural areas**	
	Diff. (%) **(1)**	**p-value** **(2)**	**Diff. (%)** **(3)**	**p-value** **(4)**	**Diff. (%)** **(5)**	**p-value** **(6)**
Panel A: Age group						
17-24 years old	0.824	0.146	0.228	0.523	0.255	0.485
25-34 years old	1.217	0.155	0.366	0.592	0.250	0.722
35-49 years old	-0.674	0.618	0.491	0.708	0.404	0.752
50-64 years old	-1.490	0.176	-1.151	0.279	-1.016	0.366
65+ years old	0.122	0.968	0.066	0.982	0.107	0.971
Panel B: Educational attainment						
Lower secondary	0.936	0.352	0.980	0.391	1.263	0.336
Upper secondary	1.112	0.381	0.743	0.607	0.033	0.982
Third level	-2.048	0.076	-1.723	0.100	-1.297	0.219
Panel C: Economic activity						
Information and communication	-0.475	0.066	-0.181	0.267	-0.184	0.253
Financial and insurance	-0.075	0.721	-0.041	0.784	-0.046	0.709
Professional, scientific and technical	-0.377	0.205	-0.493	0.056	-0.205	0.358
Education	-0.319	0.264	-0.059	0.819	0.013	0.964
Other	1.246	0.055	0.774	0.140	0.422	0.386
Panel D: Occupation						
Managers	0.099	0.723	0.085	0.751	0.098	0.713
Professionals	-2.125	0.007	-1.297	0.031	-1.115	0.056
Technicians & associate professionals	0.361	0.451	0.479	0.355	0.573	0.345
Other	1.665	0.091	0.734	0.429	0.444	0.681
Panel E: Other characteristics						
Self-employee	-0.018	0.975	-0.215	0.747	0.244	0.743
Female	-0.516	0.222	-0.290	0.416	-0.027	0.955
Partner in the same household	3.146	0.012	5.322	0.000	5.042	0.000
Parent of children under 15 years old	0.634	0.386	1.547	0.023	1.592	0.050
Full-time job	-0.824	0.457	-0.157	0.881	-0.433	0.692

Note: This table reports mean differences (percentage point changes) in regional demographic shares between 2021 and 2019 (i.e., values in 2021 minus values in 2019. Columns 1, 3, 5) and p-values for t-tests of differences in means (Columns 2, 4, 6), by cities, towns and semi-dense areas, and rural areas. For simplicity, unless indicated explicitly, the rest of the economic activities in NACE and of the occupations in ISCO-08 are subsumed under "other". The results suggest that most shares did not show significant changes across the pandemic, i.e., no significant changes in the demographic structures for the three types of areas within regions.
Source: European Union Labour Force Survey (EU-LFS).

Appendix F: Regression results

Table F.1. Who was more likely to work remotely and where? OLS regression results underlying Figures 5 and 6 and Logit regression results

Variable	2019				2020				2021			
	OLS (1)	OLS (2)	Logit (3)	Logit (4)	OLS (5)	OLS (6)	Logit (7)	Logit (8)	OLS (9)	OLS (10)	Logit (11)	Logit (12)
Age group												
[1] 25-34 years old	0.001	0.001	0.354***	0.356***	0.009**	0.009**	0.211***	0.207***	0.021***	0.021***	0.313***	0.303***
	(0.002)	(0.002)	(0.056)	(0.056)	(0.004)	(0.004)	(0.076)	(0.077)	(0.003)	(0.003)	(0.035)	(0.037)
[2] 35-49 years old	0.012***	0.012***	0.671***	0.671***	0.025***	0.025***	0.385***	0.383***	0.033***	0.034***	0.453***	0.456***
	(0.003)	(0.003)	(0.066)	(0.066)	(0.004)	(0.004)	(0.079)	(0.080)	(0.004)	(0.004)	(0.046)	(0.049)
[3] 50-64 years old	0.016***	0.016***	0.746***	0.745***	0.021***	0.022***	0.347***	0.348***	0.028***	0.028***	0.392***	0.391***
	(0.003)	(0.003)	(0.062)	(0.062)	(0.006)	(0.006)	(0.100)	(0.099)	(0.005)	(0.005)	(0.066)	(0.069)
[4] 65+ years old	0.041***	0.041***	0.989***	0.987***	0.045***	0.046***	0.566***	0.564***	0.043***	0.045***	0.529***	0.539***
	(0.008)	(0.008)	(0.085)	(0.086)	(0.009)	(0.009)	(0.115)	(0.116)	(0.007)	(0.008)	(0.082)	(0.092)
Educational Attainment												
[5] Upper secondary	0.010***	0.009***	0.275***	0.274***	0.032***	0.032***	0.663***	0.667***	0.030***	0.034***	0.665***	0.691***
	(0.002)	(0.002)	(0.052)	(0.052)	(0.003)	(0.003)	(0.079)	(0.078)	(0.003)	(0.003)	(0.062)	(0.066)
[6] Tertiary education	0.021***	0.021***	0.535***	0.532***	0.092***	0.090***	1.293***	1.273***	0.094***	0.096***	1.300***	1.302***
	(0.004)	(0.004)	(0.067)	(0.068)	(0.005)	(0.005)	(0.083)	(0.082)	(0.006)	(0.007)	(0.066)	(0.071)
Economic Activity												
[7] Information and communication	0.062***	0.062***	0.983***	0.983***	0.245***	0.243***	1.588***	1.571***	0.325***	0.319***	1.882***	1.835***
	(0.004)	(0.004)	(0.068)	(0.067)	(0.011)	(0.011)	(0.067)	(0.068)	(0.008)	(0.009)	(0.050)	(0.050)
[8] Financial and insurance	0.008***	0.008**	0.282***	0.281***	0.138***	0.135***	1.075***	1.057***	0.195***	0.193***	1.322***	1.301***
	(0.004)	(0.004)	(0.087)	(0.086)	(0.008)	(0.008)	(0.054)	(0.054)	(0.013)	(0.013)	(0.044)	(0.043)
[9] Professional, scientific and technical	0.051***	0.051***	0.563***	0.563***	0.111***	0.110***	0.735***	0.720***	0.111***	0.112***	0.723***	0.717***
	(0.004)	(0.004)	(0.041)	(0.040)	(0.006)	(0.006)	(0.042)	(0.042)	(0.006)	(0.006)	(0.030)	(0.028)
[10] Education	0.074***	0.074***	1.219***	1.219***	0.104***	0.105***	0.854***	0.865***	0.025***	0.031***	0.296***	0.332***
	(0.008)	(0.008)	(0.123)	(0.123)	(0.009)	(0.009)	(0.071)	(0.073)	(0.009)	(0.010)	(0.073)	(0.078)
Occupation												
[11] Managers	0.013***	0.013***	0.532***	0.533***	0.054***	0.052***	0.768***	0.754***	0.051***	0.052***	0.721***	0.723***
	(0.004)	(0.004)	(0.066)	(0.066)	(0.007)	(0.007)	(0.053)	(0.055)	(0.007)	(0.008)	(0.052)	(0.054)
[12] Professionals	0.047***	0.047***	0.846***	0.847***	0.108***	0.107***	1.025***	1.014***	0.123***	0.123***	1.094***	1.084***
	(0.003)	(0.003)	(0.041)	(0.041)	(0.005)	(0.005)	(0.037)	(0.037)	(0.009)	(0.009)	(0.043)	(0.044)
[13] Technical and associate professional	0.008***	0.008***	0.388***	0.388***	0.043***	0.042***	0.681***	0.674***	0.044***	0.042***	0.682***	0.664***
	(0.003)	(0.003)	(0.075)	(0.075)	(0.004)	(0.004)	(0.041)	(0.042)	(0.004)	(0.004)	(0.034)	(0.035)
Other Characteristics												
[14] Self-employed	0.162***	0.163***	2.146***	2.147***	0.107***	0.108***	0.951***	0.962***	0.079***	0.079***	0.704***	0.701***
	(0.011)	(0.011)	(0.044)	(0.044)	(0.013)	(0.013)	(0.081)	(0.081)	(0.007)	(0.007)	(0.058)	(0.059)
[15] Female	0.005***	0.005***	0.181***	0.181***	0.007***	0.007***	0.147***	0.148***	0.009***	0.009***	0.163***	0.171***
	(0.002)	(0.002)	(0.041)	(0.041)	(0.002)	(0.002)	(0.021)	(0.021)	(0.003)	(0.003)	(0.024)	(0.026)
[16] Partner in the same household	-0.002	-0.002	-0.037	-0.038	-0.001	0.003	0.032*	0.040**	0.003* (0.002)	0.004*	0.027*	0.039**
	(0.002)	(0.002)	(0.025)	(0.025)	(0.002)	(0.002)	(0.017)	(0.018)		(0.002)	(0.016)	(0.017)
[17] Parent of children under 15	0.004***	0.004***	0.065***	0.065***	-0.000	0.000	-0.009	0.001	-0.002	-0.002	-0.034*	-0.033
	(0.001)	(0.001)	(0.025)	(0.025)	(0.002)	(0.002)	(0.022)	(0.023)	(0.002)	(0.002)	(0.018)	(0.020)
[18] Full-time job	-0.008***	-0.008***	-0.125***	-0.125***	0.006***	0.006***	0.065***	0.065***	0.005	0.005	0.036	0.036
	(0.002)	(0.002)	(0.048)	(0.048)	(0.002)	(0.002)	(0.024)	(0.024)	(0.004)	(0.004)	(0.034)	(0.034)
Degree of Urbanisation												
[19] Cities		-0.002*		-0.036		0.012***		0.164***		0.020***		0.220***
		(0.001)		(0.026)		(0.004)		(0.031)		(0.003)		(0.022)
Regional Indicators												
[20] Internet speed deviation		-0.002		0.073		0.012*		0.138**		0.000		0.148**
		(0.002)		(0.046)		(0.007)		(0.051)		(0.008)		(0.059)
[21] Excess Mortality						0.128***		0.537**		0.051**		0.487**
						(0.040)		(0.247)		(0.023)		(0.207)
Country-by-month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,263,206	1,257,739	1,263,206	1,257,739	1,008,445	912,594	1,008,445	912,594	943,339	777,618	943,339	777,618
Adjust R^2	0.114	0.114	-	-	0.173	0.173	-	-	0.185	0.184	-	-
Pseudo R^2	-	-	0.220	0.220	-		0.226	0.226	-	-	0.227	0.225

Note: This table reports coefficient estimates and robust standard errors (in parenthesis) on various individual and regional factors underlying remote work uptake. The dependent variable is a dummy indicating if a respondent mainly works remotely. All regressions control for country-by-month and region-fixed effects. Robust standard errors are clustered at the TL2 level. *: Significant at 10%; **: 5%; ***: 1%.
Source: own elaboration on data from the European Union Labour Force Survey (EU-LFS), OECD.

Table F.2. Robustness check: Who was more likely to work remotely and where? Pooled OLS regressions

Variable	(1)	(2)	(3)
Age Group			
[1] 25-34 years old	0.011***	0.010***	0.016***
	(0.002)	(0.002)	(0.003)

[2] 35-49 years old	0.024***	0.024***	0.031***
	(0.003)	(0.003)	(0.004)
[3] 50-64 years old	0.023***	0.022***	0.026***
	(0.004)	(0.004)	(0.005)
[4] 65+ years old	0.043***	0.043***	0.046***
	(0.007)	(0.007)	(0.008)
Educational Attainment			
[5] Upper secondary	0.023***	0.023***	0.033***
	(0.002)	(0.002)	(0.003)
[6] Tertiary education	0.069***	0.068***	0.093***
	(0.004)	(0.004)	(0.005)
Economic Activity			
[7] Information and communication	0.218***	0.216***	0.279***
	(0.006)	(0.006)	(0.008)
[8] Financial and insurance	0.116***	0.115***	0.164***
	(0.006)	(0.006)	(0.009)
[9] Professional, scientific and technical	0.091***	0.090***	0.111***
	(0.004)	(0.004)	(0.005)
[10] Education	0.066***	0.067***	0.070***
	(0.007)	(0.007)	(0.009)
Occupation			
[11] Managers	0.038***	0.037***	0.052***
	(0.004)	(0.004)	(0.007)
[12] Professionals	0.095***	0.094***	0.116***
	(0.005)	(0.005)	(0.007)
[13] Technical and associate professional	0.032***	0.031***	0.042***
	(0.003)	(0.003)	(0.004)
Other Characteristics			
[14] Self-employed	0.115***	0.116***	0.094***
	(0.009)	(0.009)	(0.009)
[15] Female	0.007***	0.007***	0.008***
	(0.002)	(0.002)	(0.002)
[16] Partner in the same household	0.001	0.002	0.003*
	(0.001)	(0.001)	(0.002)
[17] Parent of children under 15	0.001	0.001	-0.001
	(0.001)	(0.001)	(0.002)
[18] Full-time job	0.001	0.001	0.006**
	(0.002)	(0.002)	(0.003)
Degree of Urbanisation			
[19] Cities		0.013***	0.017***
		(0.002)	(0.003)
Regional Indicators			
[20] Internet speed deviation		-0.002	0.004
		(0.006)	(0.007)
[21] Excess mortality			0.167***
			(0.022)
Country by year FE	YES	YES	YES
Region FE	YES	YES	YES
Observations	3,214,990	3,193,671	1,690,212
Adjust R^2	0.149	0.149	0.164

Note: This table reports coefficient estimates and robust standard errors (in parenthesis) on various individual and regional factors underlying remote work uptake. The dependent variable is a dummy indicating if a respondent mainly works remotely. The regressions rely on a pooled sample combining the waves conducted in 2019, 2020, and 2021. We sequentially include regional indicators in columns (2) and (3). All regressions control for country-by-year and region-fixed effects. Robust standard errors are clustered at the TL2 level. *: Significant at 10%; **: 5%; ***: 1%.
Source: own elaboration on data from the European Union Labour Force Survey (EU-LFS), OECD.

Table F.3. Who was more likely to work remotely and where? Comparing alternative definitions of remote workers

	2019			2020			2021		
Variable	Mainly	ST	Mainly+ST	Mainly	ST	Mainly+ST	Mainly	ST	Mainly+ST
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Age Group									
[1] 25-34 years old	0.001	0.014***	0.014**	0.009**	0.009*	0.018***	0.021***	0.004	0.025***
	(0.002)	(0.005)	(0.007)	(0.004)	(0.005)	(0.007)	(0.003)	(0.005)	(0.007)
[2] 35-49 years old	0.012***	0.025***	0.037***	0.025***	0.017***	0.042***	0.034***	0.016**	0.050***
	(0.003)	(0.005)	(0.008)	(0.004)	(0.005)	(0.008)	(0.004)	(0.006)	(0.009)
[3] 50-64 years old	0.016***	0.018***	0.034***	0.022***	0.012***	0.034***	0.028***	0.011**	0.040***
	(0.003)	(0.004)	(0.007)	(0.006)	(0.004)	(0.008)	(0.005)	(0.006)	(0.009)
[4] 65+ years old	0.041***	-0.007**	0.034***	0.046***	-0.004	0.041***	0.045***	-0.008	0.037***
	(0.008)	(0.003)	(0.009)	(0.009)	(0.004)	(0.010)	(0.008)	(0.006)	(0.010)
Educational Attainment									
[5] Upper secondary	0.009***	0.008	0.017***	0.032***	0.012**	0.044***	0.034***	0.023***	0.057***
	(0.002)	(0.005)	(0.007)	(0.003)	(0.005)	(0.005)	(0.003)	(0.007)	(0.008)
[6] Tertiary education	0.021***	0.055***	0.077***	0.090***	0.057***	0.147***	0.096***	0.078***	0.174***
	(0.004)	(0.009)	(0.012)	(0.005)	(0.008)	(0.010)	(0.007)	(0.008)	(0.013)
Economic Activity									
[7] Information and communication	0.062***	0.083***	0.144***	0.243***	0.037***	0.280***	0.319***	0.005	0.323***
	(0.004)	(0.006)	(0.006)	(0.011)	(0.005)	(0.010)	(0.009)	(0.009)	(0.010)
[8] Financial and insurance	0.008**	0.055***	0.063***	0.135***	0.050***	0.185***	0.193***	0.045***	0.238***
	(0.004)	(0.009)	(0.010)	(0.008)	(0.006)	(0.008)	(0.013)	(0.009)	(0.011)
[9] Professional, scientific and technical	0.051***	0.036***	0.087***	0.110***	0.035***	0.145***	0.112***	0.044***	0.156***
	(0.004)	(0.006)	(0.004)	(0.006)	(0.004)	(0.006)	(0.006)	(0.004)	(0.007)
[10] Education	0.074***	0.068***	0.142***	0.105***	0.054***	0.159***	0.031***	0.075***	0.106***
	(0.008)	(0.007)	(0.009)	(0.009)	(0.007)	(0.009)	(0.010)	(0.009)	(0.008)
Occupation									
[11] Managers	0.013***	0.136***	0.149***	0.052***	0.110***	0.162***	0.052***	0.143***	0.195***
	(0.004)	(0.014)	(0.014)	(0.007)	(0.009)	(0.013)	(0.008)	(0.012)	(0.013)
[12] Professionals	0.047***	0.094***	0.141***	0.107***	0.072***	0.179***	0.123***	0.090***	0.214***
	(0.003)	(0.010)	(0.012)	(0.005)	(0.008)	(0.010)	(0.009)	(0.007)	(0.012)
[13] Technical and associate professional	0.008***	0.026***	0.034***	0.042***	0.034***	0.076***	0.042***	0.054***	0.096***
	(0.003)	(0.004)	(0.006)	(0.004)	(0.004)	(0.006)	(0.004)	(0.005)	(0.007)
Other Characteristics									
[14] Self-employed	0.163***	0.073***	0.236***	0.108***	0.054***	0.162***	0.079***	0.062***	0.142***
	(0.011)	(0.011)	(0.010)	(0.013)	(0.011)	(0.010)	(0.007)	(0.005)	(0.010)
[15] Female	0.005***	-0.014***	-0.009***	0.007***	-0.009***	-0.002	0.009***	-0.006***	0.004
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.001)	(0.003)
[16] Partner in the same household	-0.002	0.010***	0.008	0.003	0.007*	0.009**	0.004*	0.009*	0.013*
	(0.002)	(0.003)	(0.005)	(0.002)	(0.004)	(0.004)	(0.002)	(0.005)	(0.007)
[17] Parent of children under 15	0.004***	0.009***	0.013***	0.000	0.008***	0.008***	-0.002	0.002	0.000
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
[18] Full-time job	-0.008***	0.019***	0.011*	0.006***	0.018***	0.024***	0.005	0.030***	0.036***
	(0.002)	(0.004)	(0.006)	(0.002)	(0.005)	(0.006)	(0.004)	(0.004)	(0.007)
Degree of Urbanisation									
[19] Cities	-0.002*	0.011***	0.009***	0.012***	0.008***	0.021***	0.020***	-0.001	0.019***
	(0.001)	(0.002)	(0.002)	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
Regional Indicators									
[20] Internet speed deviation	-0.002	-0.012***	-0.010***	0.012*	-0.009***	0.003	0.000	0.009***	0.009
	(0.002)	(0.003)	(0.003)	(0.007)	(0.003)	(0.006)	(0.008)	(0.003)	(0.008)
[21] Excess mortality				0.128***	-0.056*	0.072***	0.051**	-0.016	0.035*
				(0.040)	(0.033)	(0.019)	(0.023)	(0.023)	(0.019)
Country by month FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Region FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Observations	1,257,739	1,257,739	1,257,739	912,594	912,594	912,594	777,618	777,618	777,618
Adjust R^2	0.114	0.143	0.242	0.173	0.107	0.266	0.184	0.122	0.300

Note: This table reports coefficient estimates and robust standard errors (in parenthesis) on various individual and regional factors underlying remote work uptake. The dependent variables in columns (1), (4) and (7) are a dummy indicating if a respondent 'mainly' works remotely, as in the main analysis of Table F.1. The dependent variables in columns (2), (5), and (8) are a dummy indicating if a respondent 'sometimes' ('ST') works remotely. The dependent variables in columns (3), (6), and (9) are a dummy indicating if a respondent 'sometimes' or 'mainly' works remotely. All regressions control for country-by-month and region-fixed effects. Robust standard errors are clustered at the TL2 level. *: Significant at 10%; **: 5%; ***: 1%.
Source: own elaboration on data from the European Union Labour Force Survey (EU-LFS), OECD.

Table F.4. Within-region urban-rural gaps in the share of remote workers, by occupations

Occupation Category	Year	Urban-rural Gap		Mean share	Observations
(1)	(2)	(3)	(4)	(5)	(6)
A. Managers	2019	-0.002	(0.005)	0.094	66,865
	2020	0.026***	(0.010)	0.152	46,895
	2021	0.038***	(0.009)	0.154	40,899
B. Professionals	2019	-0.005	(0.004)	0.116	247,675
	2020	0.021***	(0.006)	0.249	188,753
	2021	0.038***	(0.006)	0.245	167,787
C. Technicians and Associate Professionals	2019	0.003	(0.002)	0.051	206,155
	2020	0.022***	(0.006)	0.136	140,718
	2021	0.030***	(0.005)	0.139	125,137
D. Clerical Support Workers	2019	-0.002	(0.002)	0.027	126,965
	2020	0.032***	(0.004)	0.113	88,530
	2021	0.036***	(0.008)	0.137	74,867
E. Services and Sales Workers	2019	-0.002	(0.002)	0.030	225,108
	2020	-0.004	(0.003)	0.035	161,958
	2021	-0.002	(0.003)	0.038	129,278
F. Craft and Related Trades Workers	2019	-0.002	(0.001)	0.020	166,596
	2020	0.001	(0.002)	0.022	122,645
	2021	0.002	(0.003)	0.019	103,836
G. Plant and Machine Operators and Assemblers	2019	-0.001	(0.001)	0.008	109,288
	2020	-0.003*	(0.002)	0.006	83,244
	2021	-0.001	(0.001)	0.006	71,798
H. Elementary Occupations	2019	-0.004***	(0.001)	0.008	107,218
	2020	0.002	(0.002)	0.008	75,744
	2021	-0.001	(0.002)	0.007	61,855

Note: This table reports coefficient estimates (column 3) and robust standard errors (column 4, in parenthesis) on within-region urban-rural gaps in the share of remote workers, by occupation (ISCO 1 digit with Skilled Agricultural, Forestry and Fishery Workers excluded) and year. We regress a dummy indicating if a respondent mainly works remotely on the *City* dummy for subsamples separated by occupation and year, conditional on country-by-month and region-fixed effects. In addition, all regressions control for sociodemographic characteristics (age, sex, education, self-employment status, whether partner is in the same household, whether having children under 15 years, whether taking full-time jobs, industry dummies), and regional indicators (internet speed deviation, excess mortality) where applicable. Robust standard errors are clustered at the TL2 level. *: Significant at 10%; **: 5%; ***: 1%.
Source: own elaboration on data from the European Union Labour Force Survey (EU-LFS), OECD.

Table F.5. Remote work uptake across age groups, by degree of urbanisation and gender

	2019	2020	2021
	(1)	(2)	(3)
Panel A: Degree of urbanisation			

25-34 years old	0.021***	0.040***	0.056***
	(0.002)	(0.004)	(0.004)
35-49 years old	0.038***	0.061***	0.077***
	(0.002)	(0.005)	(0.005)
50-64 years old	0.043***	0.056***	0.066***
	(0.002)	(0.004)	(0.005)
65+ years old	0.124***	0.125***	0.107***
	(0.006)	(0.008)	(0.010)
Cities	0.006***	0.022**	0.032***
	(0.003)	(0.001)	(0.006)
25-34 years old × Cities	0.003	0.042***	0.049***
	(0.003)	(0.011)	(0.007)
35-49 years old × Cities	0.004	0.030***	0.028***
	(0.003)	(0.009)	(0.007)
50-64 years old × Cities	0.002	0.011	0.005
	(0.003)	(0.010)	(0.006)
65+ years old × Cities	0.000	0.009	0.031**
	(0.004)	(0.012)	(0.014)
Observations	1,426,093	1,179,494	1,067,267
Adjust R^2	0.024	0.060	0.069
Panel B: Gender			
25-34 years old	0.021***	0.058***	0.076***
	(0.001)	(0.005)	(0.006)
35-49 years old	0.036***	0.066***	0.082***
	(0.002)	(0.005)	(0.006)
50-64 years old	0.042***	0.059***	0.067***
	(0.002)	(0.005)	(0.005)
65+ years old	0.129***	0.137***	0.122***
	(0.007)	(0.009)	(0.008)
Female	0.000	0.007*	0.005
	(0.002)	(0.004)	(0.004)
25-34 years old × Female	0.003*	0.003	0.006
	(0.002)	(0.005)	(0.005)
35-49 years old × Female	0.008***	0.016***	0.014**
	(0.002)	(0.005)	(0.006)
50-64 years old × Female	0.003	0.003	-0.001
	(0.002)	(0.006)	(0.007)
65+ years old × Female	-0.012	-0.019**	-0.003
	(0.009)	(0.008)	(0.006)
Observations	1,426,093	1,179,494	1,067,267
Adjust R^2	0.024	0.057	0.064
Country-by-month FE	YES	YES	YES
Region FE	YES	YES	YES

Note: This table reports coefficient estimates and robust standard errors (in parenthesis) on interaction terms (and separate terms) between age group dummies and a city dummy (Panel A) or a female dummy (Panel B). All regressions control for country-by-month and region-fixed effects. Robust standard errors are clustered at the TL2 level. *: Significant at 10%; **: 5%; ***: 1%. Source: own elaboration on data from the European Union Labour Force Survey (EU-LFS).

Table F.6. Motherhood effects on remote work

Variable	2019 (1)	2020 (2)	2021 (3)
Female	0.004**	0.006***	0.008***
	(0.002)	(0.002)	(0.002)
Parent of children under 15	0.002	-0.000	-0.004
	(0.001)	(0.002)	(0.003)
Female × Parent of children under 15	0.003**	0.001	0.003
	(0.002)	(0.002)	(0.003)
Demographics	YES	YES	YES
Regional indicators	YES	YES	YES
Country by month FE	YES	YES	YES
Region FE	YES	YES	YES
Observations	1,257,739	912,594	777,618
Adjust R^2	0.114	0.173	0.184

Note: This table examines motherhood effects on remote work by regressions of remote work status on interactions between the female dummy and the parent dummy, conditional on a range of demographic characteristics and regional indicators. Demographic characteristics include age, gender, educational attainment, economic activity, occupation, self-employed status, status of parent of children under 15, status of having partner in the same household, status of taking full-time jobs. Regional indicators include city dummy, internet speed deviation, and excess mortality where applicable. In addition, we control for a full set of country by month and region fixed effects. Robust standard errors are clustered at the TL2 level. *: Significant at 10%; **: 5%; ***: 1%.
Source: own elaboration on data from the European Union Labour Force Survey (EU-LFS), OECD.

Table F.7. Who was more likely to work remotely and where? Dropping Fixed Effects

	2019	2020		2021	
Variable	(1)	(2)	(3)	(4)	(5)
Age Group					
[1] 25-34 years old	0.000	0.009**	0.010**	0.022***	0.023***
	(0.002)	(0.004)	(0.004)	(0.004)	(0.004)
[2] 35-49 years old	0.012***	0.025***	0.025***	0.034***	0.035***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
[3] 50-64 years old	0.016***	0.021***	0.022***	0.028***	0.030***
	(0.003)	(0.006)	(0.006)	(0.005)	(0.005)
[4] 65+ years old	0.041***	0.046***	0.046***	0.046***	0.045***
	(0.008)	(0.009)	(0.009)	(0.009)	(0.008)
Educational Attainment					
[5] Upper secondary	0.010***	0.031***	0.031***	0.032***	0.031***
	(0.002)	(0.004)	(0.003)	(0.004)	(0.004)
[6] Tertiary education	0.021***	0.089***	0.089***	0.094***	0.095***
	(0.004)	(0.005)	(0.005)	(0.007)	(0.007)
Economic Activity					
[7] Information and communication	0.062***	0.245***	0.245***	0.324***	0.327***
	(0.004)	(0.011)	(0.011)	(0.009)	(0.010)
[8] Financial and insurance	0.009**	0.138***	0.139***	0.198***	0.202***
	(0.004)	(0.008)	(0.008)	(0.013)	(0.013)
[9] Professional, scientific and technical	0.051***	0.111***	0.111***	0.115***	0.115***
	(0.004)	(0.006)	(0.006)	(0.007)	(0.007)
[10] Education	0.073***	0.104***	0.104***	0.030***	0.033***
	(0.008)	(0.009)	(0.009)	(0.010)	(0.011)
Occupation					
[11] Managers	0.013***	0.053***	0.053***	0.054***	0.057***
	(0.004)	(0.007)	(0.007)	(0.008)	(0.009)
[12] Professionals	0.047***	0.109***	0.109***	0.126***	0.128***
	(0.003)	(0.005)	(0.006)	(0.009)	(0.010)
[13] Technical and associate professional	0.008***	0.042***	0.043***	0.043***	0.044***
	(0.003)	(0.004)	(0.004)	(0.004)	(0.004)
Other Characteristics					
[14] Self-employed	0.162***	0.108***	0.107***	0.079***	0.076***
	(0.011)	(0.013)	(0.013)	(0.007)	(0.007)
[15] Female	0.005***	0.007***	0.007***	0.009***	0.010***
	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
[16] Partner in the same household	-0.002	0.002	0.002	0.003	0.002
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
[17] Parent of children under 15	0.004***	0.000	0.000	-0.002	-0.002
	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
[18] Full-time job	-0.008***	0.005**	0.006**	0.006	0.006
	(0.002)	(0.002)	(0.002)	(0.004)	(0.004)
Degree of Urbanisation					
[19] Cities	-0.002*	0.016***	0.015***	0.026***	0.026***
	(0.001)	(0.003)	(0.003)	(0.003)	(0.004)
Regional Indicators					
[20] Internet speed deviation	0.002	0.009	0.011**	0.013*	0.015**
	(0.002)	(0.006)	(0.005)	(0.007)	(0.007)
[21] Excess mortality		0.119***	0.096***	0.005	-0.000
		(0.028)	(0.025)	(0.052)	(0.037)
[22] Stringency index			0.001***		0.002***
			(0.000)		(0.000)
Country by month FE	YES	YES	NO	YES	NO
Country FE	NO	NO	YES	NO	YES
Region FE	NO	NO	NO	NO	NO
Observations	1,257,739	912,594	912,594	777,618	711,454
Adjust R^2	0.113	0.170	0.161	0.178	0.176

Note: This table reports coefficient estimates and robust standard errors (in parenthesis) on various individual and regional factors underlying remote work uptake. The dependent variables are a dummy indicating if a respondent ‘mainly’ works remotely. Columns (1), (2), and (4) only control for country-by-month fixed effects. Columns (3) and (5) only control for country fixed effects, and further add stringency index as a control. Robust standard errors are clustered at the TL2 level. *: Significant at 10%; **: 5%; ***: 1%.

Source: own elaboration on data from the European Union Labour Force Survey (EU-LFS), OECD.

Appendix G: Explaining the gap in remote work uptake between cities and other areas

This appendix reports the adjusted R^2s of the regressions underlying the results presented in Figure 7. Overall, Model 5 allows explaining around 18.0% of the variation in individual remote work uptake. Confirming the findings highlighted in Figure 7, the largest increase in the explanatory power of the model occurs when including the individual regressors.

Table G.1. How much variation in the urban-rural gap in remote work uptake can be explained?

Year	2019	2020	2021
No control	0.069%	0.746%	1.063%
Country-by-month FE	1.664%	4.960%	5.446%
Country-by-month FE + Region FE	1.782%	5.652%	6.482%
Country-by-month FE + Region FE + Individual factors	11.413%	17.320%	18.596%
Country-by-month FE + Region FE + Individual factors + Regional factors	11.418%	17.281%	18.380%

Note: This table reports the adjusted R squares from the five regression models underlying Figure 7. Model 1 regresses the remote work dummy on a city dummy alone. Model 2 further controls for country-by-month fixed-effects. Model 3 further controls for region fixed-effects. Model 4 then adds the individual regressors, while Model 5 further controls for regional characteristics. In all regressions, standard errors are clustered at the TL2 level.
Source: own elaboration on data from the European Union Labour Force Survey (EU-LFS), OECD.