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The new geography of remote jobs? Evidence from Europe

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The COVID-19 pandemic has led to a dramatic acceleration in the diffusion of remote work. This paper contributes to understanding the phenomenon by offering the first systematic exploration of the uneven diffusion of remote jobs across Europe. Using a combination of rich individual micro-data from the European Union Labour Force Survey and regional-level characteristics, the analysis makes three contributions. First, it provides a systematic approach to measure remote work across 30 European countries. Second, it shows that cities and capital regions adapted faster to remote work than other areas of the continent. Third, it identifies and tests what factors are associated with telework uptake during the pandemic. Results show that the uneven diffusion of remote work is primarily explained by composition effects, i.e., because cities hosted more workers in occupations and sectors more amenable to working remotely.

Keywords: work from home; remote work; telework; COVID-19; Europe
JEL codes: I18; J20; O52; P25

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Acknowledgements

This paper benefited from helpful comments at various stages from Ricardo Crescenzi (LSE), Michael Koelle (OECD, Economics Department), Franziska Sielker (TU Wien) and Paolo Veneri (Gran Sasso Science Institute). Thanks are also due to Nadim Ahmad, Rüdiger Ahrend, David Burgalassi, Michelle Marshalian, Ana Moreno Monroy, Wessel Vermeulen, Alison Weingarden (all OECD, Centre for Entrepreneurship, SMEs Regions and Cities, CFE). Jasper Hesse (OECD/CFE) provided statistical support.

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1 Introduction

The COVID-19 pandemic has led to a dramatic acceleration in the expansion of remote work across many advanced economies. Yet, despite growing interest in the implications of working remotely for cities and regions, little is still known about the actual new geography of remote jobs during the pandemic.

There has been a growing debate on whether the extensive observed uptake in remote work will lead to a structural relocation of workers and advanced economic activities from core urban areas towards less dense areas (Nathan and Overman, 2020[1]; Florida, Rodríguez-Pose and Storper, 2021[2]; Althoff et al., 2022[3]; Glaeser, 2021[4]; Grabner and Tsvetkova, 2022[5]; Fiorentino et al., 2022[6]). Yet, across most OECD countries, it is still unclear which are the areas where workers transitioned fastest to remote work. Similarly, there is limited evidence about what individual and territorial factors are associated with remote work uptake, and whether these features are evenly spread across space or concentrated in specific areas.

This paper investigates the new geography of remote jobs across the regions and cities of Europe and examines for the first time the individual and territorial determinants of the geographical distribution of remote work in the context of the COVID-19 pandemic.

Addressing these issues is essential from a policy perspective, as it will allow better understanding of the factors that hinder achieving the full potential benefits associated with remote work, especially in areas where its uptake is still limited (Eurofound, 2020[7]). Growing evidence suggests that remote work capacity will indeed play a key role in the evolution of regional inequality and development in the future (Stantcheva, 2022). The paper makes three main contributions.

First, it develops a new measure of *actual* remote work consistently for European countries, exploiting microdata from the annual waves of the European Union (EU) Labour 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 covering 30 European countries. The increase in remote work captured by the measurement closely follows governments' lockdown policies during the pandemic and is positively correlated with the pre-pandemic measurements of remote work potential proposed by Dingel & Neiman (2020[8]) and applied to European regions by OECD (2020[9]).

The data show that the remote work uptake during the pandemic was markedly uneven across and within European countries. Most places with higher levels of remote work before the pandemic also experienced a faster uptake afterwards. Moreover, on average, workers living in capital regions and urban centres experienced the highest uptake. While the share of remote workers across all European regions rose on average from 5.4% in 2019 to 14% in 2021, it almost quadrupled in capital regions, increasing from 6% to 22%. Over the same period the share of remote workers more than tripled in cities, while it only doubled in towns and semi dense-areas and rural areas.

Second, drawing on recent literature, the paper identifies and explores individual and territorial drivers of remote work uptake during the pandemic. Results show that the workers who adopted remote work tended to be older, self-employed, and with higher levels of formal education. They also tended 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. Unexpectedly, but in line with recent literature, the results do not point to significant gender differences in remote work uptake during the pandemic, after adjusting for other individual characteristics (e.g., occupation) and industry. At the territorial level, the results 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 decreased in 2021.

Third, the analysis implements the decomposition procedure proposed by Gelbach (2016[10]) to identify what is the relative role of contextual vs composition factors in explaining the identified remote work gap between cities and other areas. Overall, while both composition and contextual regressors are relevant predictors, the analysis suggests that workers and industrial composition play a larger role than territorial factors. For example, the individual characteristics (e.g., education, age, occupation) and industry of employment 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.

The remainder of the paper is structured as follows. Section 2 reviews the existing literature on the nature and determinants of remote work uptake. Section 3 discusses the data sources and describes the proposed measures of remote work and their validity. Next, section 4 documents the changes in the geography of remote work throughout the pandemic. Section 5 empirically tests, for European workers, the contribution of potential enabling/inhibiting factors to the likelihood of working remotely during the pandemic. The last section concludes.

2 The expansion of remote work: Existing evidence

COVID-19 and the uneven geographical expansion of remote work

The outbreak of the COVID-19 pandemic led to a dramatic acceleration in the expansion of remote work. 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[11]). 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., 2021[12]). 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. Similarly, between February and December 2020 Australia witnessed a 15 percent point increase. Noteworthy rises in remote work uptake have also been recorded across emerging and middle-income countries (Gottlieb et al., 2021[13]).

Importantly, while much remains to be uncovered, the existing evidence suggests that the geographical distribution of remote work *potential* and *actual uptake* has been markedly uneven. At the outset of the pandemic when data on remote job practices was unavailable, Dingel & Neiman (2020[8]) proposed a measure of remote work potential based on the task content of occupations to classify jobs that are amenable to working remotely (see Appendix B for further details). Following this approach, a strand of recent literature highlights that the geography of remote work *potential* is markedly unbalanced (Althoff et al., 2022[3]). For example, OECD (2020[9]) explores data for 27 European countries, Switzerland, Turkey and the US. They find large differences in the potential to work remotely between urban and rural areas.

New data allow researchers to explore patterns of *actual remote work* since the COVID-19 pandemic. (Althoff et al., 2022[3]) analyse the geography of remote work across US cities and show that metropolitan areas witnessed the highest growth of actual remote work uptake during the pandemic. Complementing research on the uptake of remote work in US regions, this paper provides evidence of the differences in RW across OECD regions in other/European countries.

This paper aims to explain the factors that drive the geographical differences in remote work uptake across the European continent. Building on the existing literature, the analysis focuses on two main hypotheses, respectively linked to compositional and contextual effects. The compositional hypothesis suggests that the spatial differences in remote work uptake can be explained by the differences in the sectoral and workforce composition across places (i.e., by the geographically heterogeneous distribution of people with different characteristics). By contrast, the contextual hypothesis highlights how geographical differences in remote work uptake may be linked to place-specific territorial factors (e.g., broadband infrastructure, internet speed) that may enable/inhibit workers to switch to remote work. The following sections discuss each hypothesis in detail.

Is the geography of remote work linked to sectoral or 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 (Adrjan et al., 2021[14]; Adrjan et al., 2023[15]; Criscuolo et al., 2021[16]; OECD, 2021[17]). 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 (Adams-Prassl et al., 2022[18]). Since such industries and jobs tend to concentrate in cities, these places are 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[18]; OECD, 2021[17]).

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[18]) 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, Garrote Sanchez et al. (2021[19]) 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[20]) also claim the absence of any difference across genders in remote work across the EU. Other complicating factors reflect the fact that women have historically been more likely to stay at home for child and family care needs, especially in countries with more traditional and patriarchal social norms. As such, during the pandemic, remote work may have been used by women more than by 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 (Garrote Sanchez et al., 2021[19]; Dingel and Neiman, 2020[8]).

Do contextual factors influence 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. The internet has allowed many jobs to be conducted remotely, even in sectors where physical presence was historically 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[21]).

Yet, there are significant differences in the digital infrastructure both within and across many countries (Vilhelmson and Thulin, 2001[22]; OECD, 2022[23]). As an 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 (OECD, 2023[24]).

Second, the suitability of home conditions to remote work can also matter. Cuerdo-Vilches et al. (2021[25]) suggest that having a more spacious home with dedicated workspace, or a 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 lower.

Third, the decision to take up remote work may be closely related to the local impact of the pandemic, as workers living in areas hit more severely by the pandemic might have, in response, been more willing – or forced – to stay at home to avoid the virus (Diaz Ramirez, Veneri and Lembcke, 2021[26]). The severity of the pandemic, captured through the excess mortality, was strikingly uneven across the subnational regions of OECD member states (Diaz Ramirez, Veneri and Lembcke, 2021[26]).

In summary, while remote work surged because of the pandemic, evidence of its geographical expansion remains scarce outside of specific cases such as the US. Differences in uptake may be driven by the composition or contextual factors. The remainder of the analysis will test these alternative hypotheses empirically.

3 Data and the measurement of remote work across Europe

This section presents the data used in the analysis and provides a new measure of *actual* remote work consistently for European countries.

Overview of 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,[1] 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 27 Member States of the EU (that is, all EU27 countries), plus Norway, Switzerland, and Iceland.[2] 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.

The annual survey is carried out on a rolling basis, and respondents are interviewed every month. 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. The current research focuses on WFH. 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. In particular, the survey records whether respondents: (1) "mainly work at home"; (2) "sometimes work at home"; (3) "never work at home", in their main job. 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"

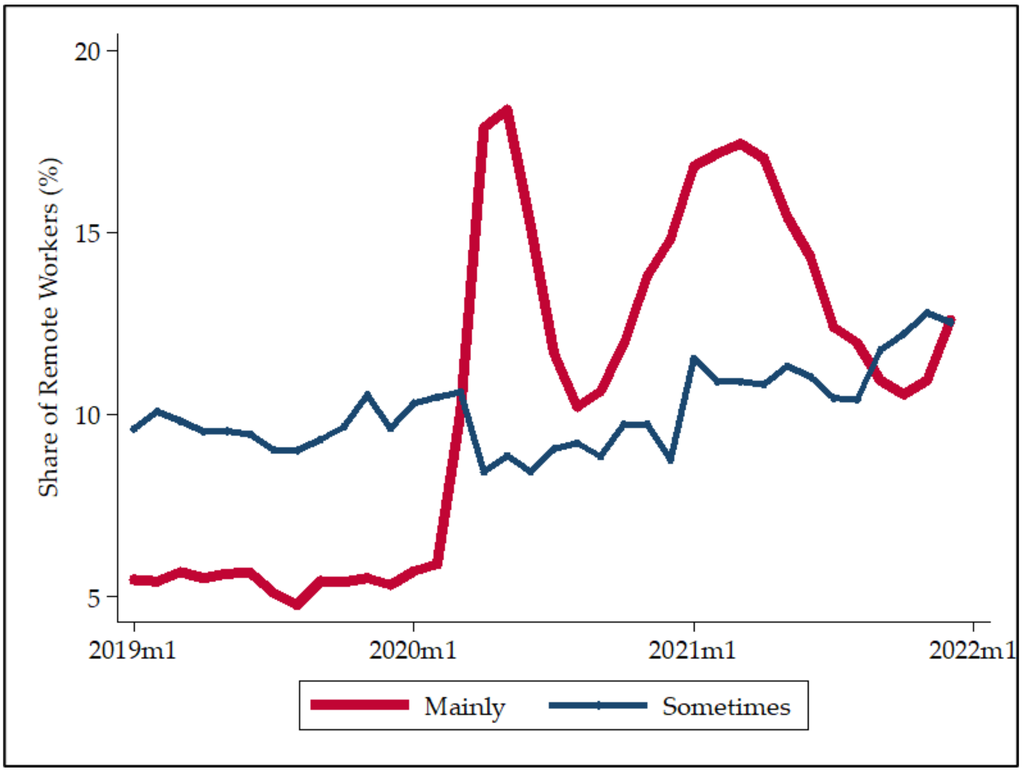
1 The EU-LFS is representative at the Eurostat NUTS2 level. For most European countries, NUTS2 regions correspond to the OECD TL2 classification. In Belgium, France, and Germany, however, NUTS2 do not exactly correspond to TL2 regions, but are a tier between TL2 and TL3. In these cases, the current analysis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

2 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.

denotes working at home on no occasion. Second, despite the growing relative importance of co-working spaces, their absolute share as workplaces is still modest overall.

While it is difficult to clearly ascertain who are remote workers among the respondents who "mainly" work from home, as opposed to "sometimes", the current analysis assumes that the former are "remote workers", while the latter are involved in "hybrid work".[3] Figure 3.1 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 only moderately increased. By contrast, the share of those "mainly" working remotely almost tripled after the onset of the pandemic, rising from 5.5% in 2019 to 14% over 2021, peaking at 18.5% in May 2020.[4]

Figure 3.1. 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).

3 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.

4 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% (Althoff et al., 2022[3]). 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%.

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.5 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 (Annex Figure 1 and Annex Figure 2).

Across most countries remote work uptake is closely linked to governmental lockdown policies. Annex Figure 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[27]) to measure the stringency of government lockdown policies during the pandemic.[6] The plots confirm how a majority of countries – such as Austria, Denmark, France, and Germany – experienced a peak in their shares of remote workers in April/May 2020, when their respective governments imposed the most stringent restrictions.[7]

Annex C 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.

To ascertain the extent to which our measure of *actual regional remote work* correlates to measures of regional remote work *potential*, the analysis calculates a measure of potential following the approach of Dingel & Neiman (2020[8]) for the US. (See Appendix B for details on how it is calculated.) 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 A, were mostly associated with remote work uptake. These industries are “information and communication”, “finance and insurance”, “professional, scientific and technical services”, and “education”,

5 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.

6 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.

7 These findings are also consistent with Adrjan et al. (2021[14]) who find a similar relationship between remote work uptake and overall stringency of policy measures across other OECD countries. Annex Table 6 and Annex Table 7 replicate the exercise respectively replacing the overall stringency index with two of its sub-components.

while the occupations include managers, professionals, and associate professionals.[8] Finally, the EU-LFS also reports the degree of urbanisation of where each respondent lives.[9]

Annex Table 3 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 the TL2 region where their residence is located.[10] It is therefore possible to measure the remote work uptake at the regional level and match the EU-LFS data to other territorial information. 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 Diaz Ramirez et al., (2021[26]). Internet speed data are collected quarterly for each region and, within each subnational region, are disaggregated by degree of urbanisation. The analysis measures the local internet speed (by degree of urbanisation and region) as the deviation from the national average in that year.[11] Excess mortality data measures monthly excess deaths at the regional level in 2020 and 2021 and is a proxy for capturing the severity of the pandemic in each region. The analysis matches the two regional level variables with the EU-LFS data by region, degree of urbanisation, and time (where applicable).[12]

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

9 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.

10 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.

11 In contrast to the EU-LFS, data on internet speed deviation and excess mortality are available at TL1 and TL2 levels. On both variables, 4 observations can only be matched for TL1 regions. The data on excess mortality is available and can be matched to 186 TL2 regions. 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.

12 Since internet speed deviation has little variation across quarter, the analysis calculates 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, excess mortality is matched with the EU-LFS by region and month (excess mortality information is not available at the degree of urbanisation level).

Annex Table 4 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 that the national average. In 2021, the gap in internet speed increased between cities and towns and semi-dense areas but reduced between cities and rural areas.

4 The uneven geographical expansion of remote work

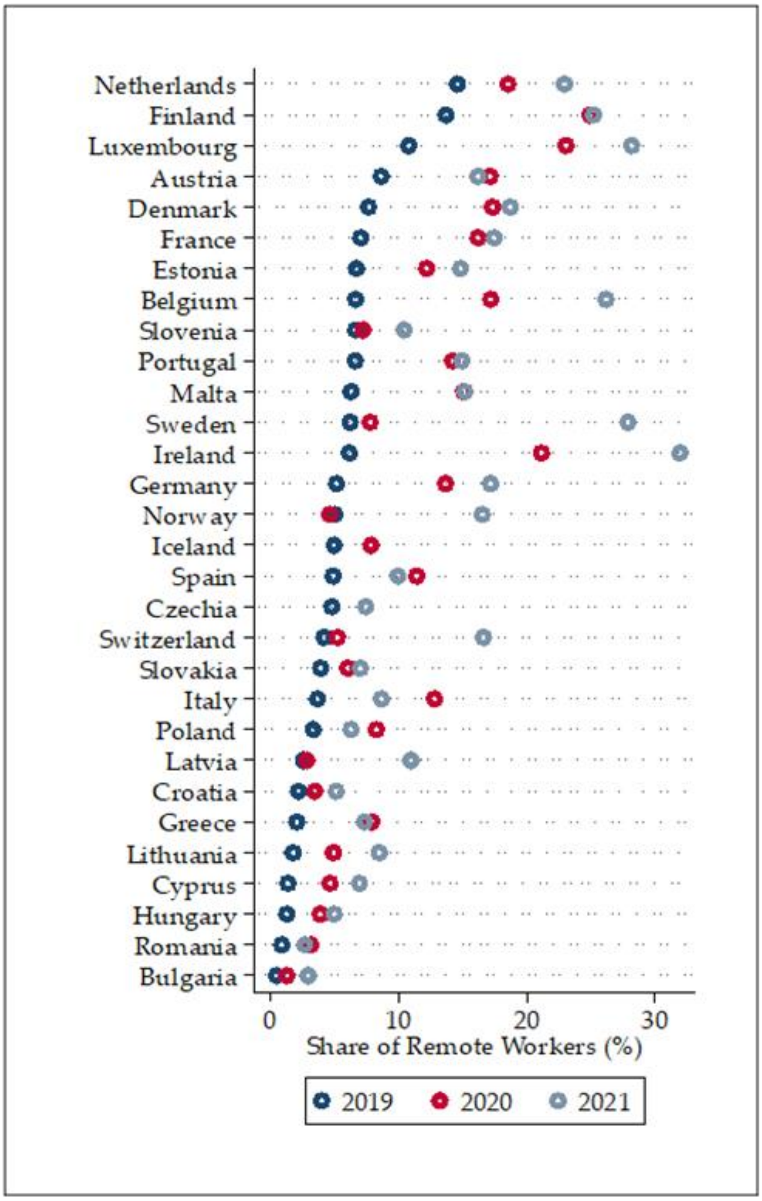
This section maps the geographical distribution of remote work uptake in Europe between 2019 and 2021. It first provides a country-level overview, followed by a more detailed analysis at the TL2 level, while also distinguishing between areas at different degrees of urbanisation. The evidence shows an overall level of path-dependency in the spread of remote work. The areas with a higher share of remote workers in 2019 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 country

Since the outbreak of the pandemic, almost all countries experienced increases in the spread of remote work. However, this increase has been markedly uneven across countries. Figure 4.1 plots the shares of remote workers for each of the 30 countries covered by the data. Countries are ordered vertically by their 2019 shares.

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.

Figure 4.1. Shares of remote workers by country, 2019 to 2021

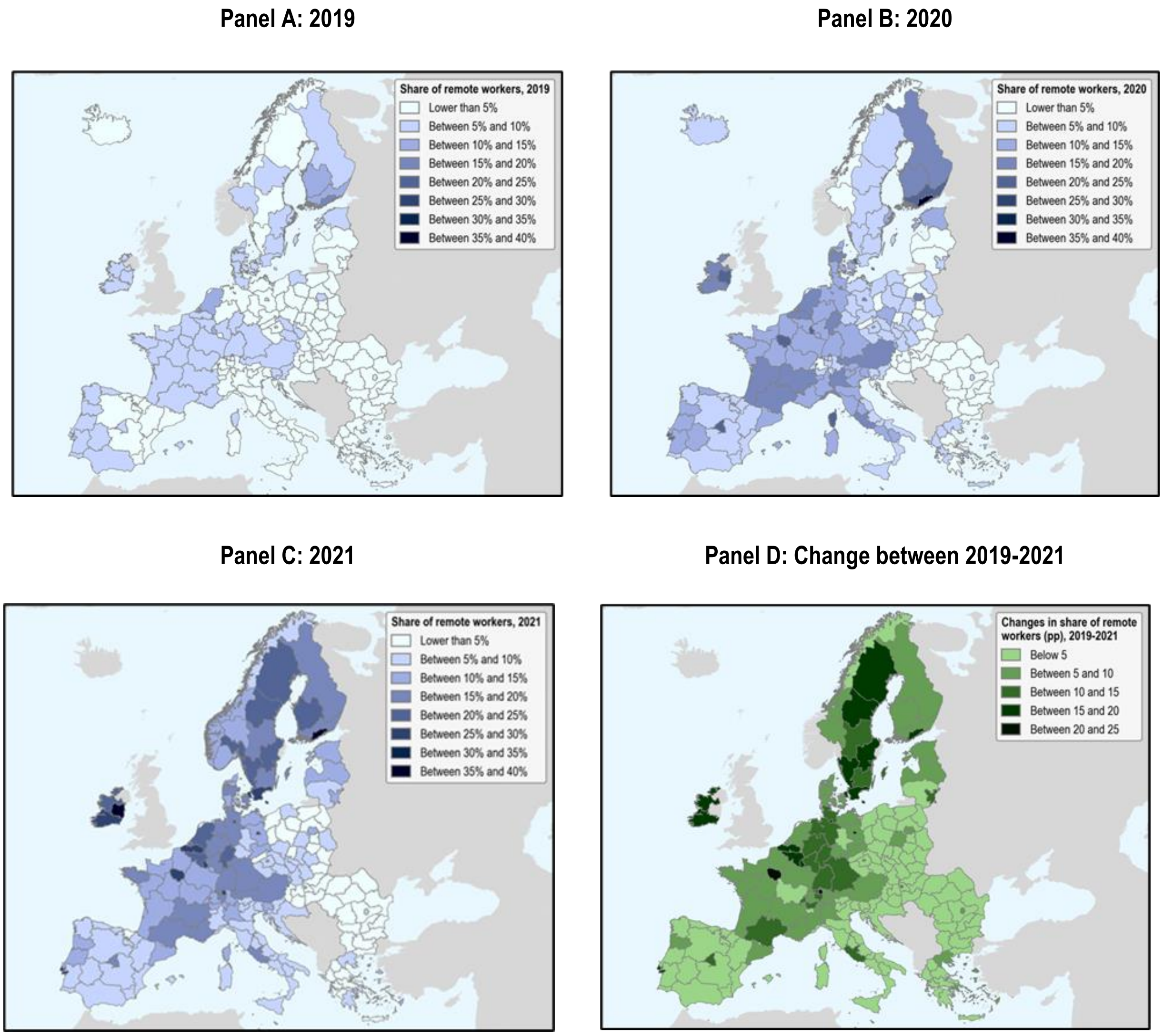


Note: This figure plots the shares of respondents working remotely for 30 European countries. It shows that the shares increased for most countries, and that the increases have tended, in general, to be proportional to initial levels.
Source: European Union Labour Force Survey (EU-LFS).

Results by TL2 regions

During the pandemic regions diverged in their shift to remote work. Figure 4.2 maps the high spatial heterogeneity in the rates of remote work uptake.

Figure 4.2. Regional share of remote workers by TL2 regions, 2019 to 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.
Source: European Union Labour Force Survey (EU-LFS).

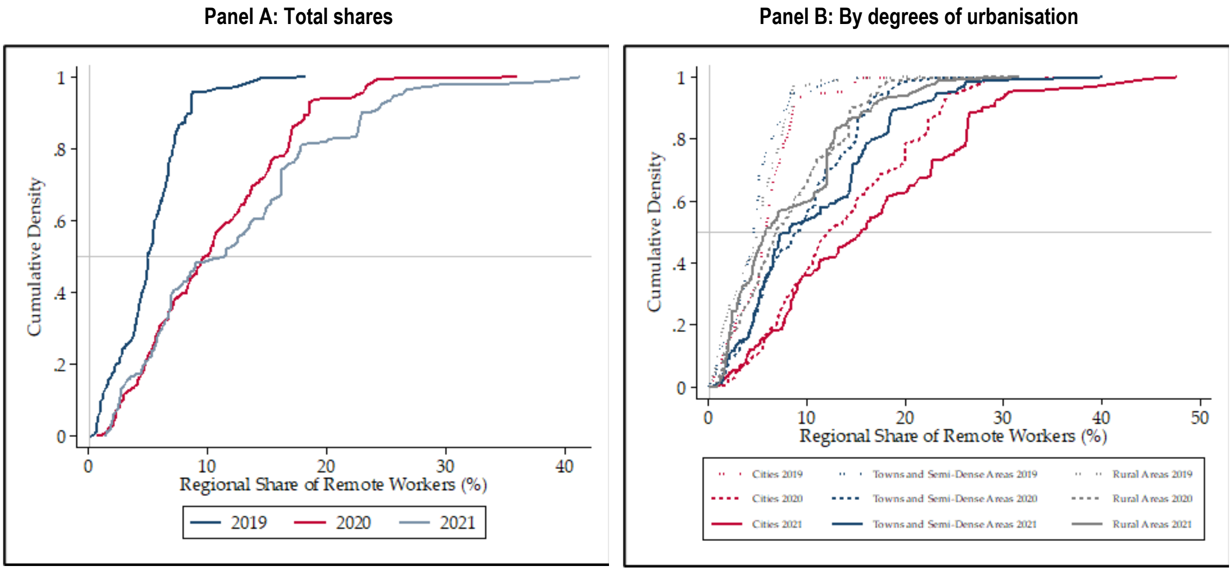
It shows the shares of remote workers across European TL2 regions (except for Austria, Netherlands, Iceland, and Croatia, where subnational information is unavailable) in 2019 (Panel A), 2020 (Panel B), 2021 (Panel C), as well as the changes in absolute percentage points over the three years (Panel D). 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 are 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.[13]

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.[14]

Figure 4.3. Cumulative distribution functions of regional share of remote workers, 2019 to 2021



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).

13 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.

14 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 5.3. 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.

Figure 4.3 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 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 of respondents' place of residence. 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.

5 Individual vs territorial factors and the geography of remote work

The previous section highlighted the uneven changes in the geography of remote work uptake. This section aims to test what factors explain such heterogeneity. It does so by analysing the extent to which 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 policies to support people and places where the remote work uptake is limited.

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.[15]

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[16] industries, two-digit ISCO-08[17] occupations, employment status (being employed, and having a full-time job), 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.[18]

15 In other words, since the survey is a repeated cross-section, it is not possible to exploit the panel dimension and run an individual-level model where the outcome is measured in changes rather than levels.

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

17 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.

18 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.

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).[19]

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 factors (e.g., differences in climate and natural amenities, infrastructure or local government quality, etc.), the matrix $RegChar'_{rm}$ includes two key regional factors: internet speed and excess mortality rates during the pandemic. Internet speed is measured as the deviation in the local internet speed (in each TL2 region and by the degree of urbanisation), from the national average in that 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. However, it should be noted that the measure captures both the instantaneous and lagged effect of the severity of the pandemic. Consequently, workers in areas exposed to more severe health consequences during the pandemic (i.e., 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. (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.)

Lastly, the regressions control for country-by-month fixed-effects α_{cm} to account for country-specific 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.

The pandemic may have caused workers able to work remotely to relocate from cities to less densely-populated areas (cf. Ramani and 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.[20] 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 temporary structural change in the composition of the workforce in/out of cities due to lockdowns. 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 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 $PerChar'$, Annex Table 5 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

19 The analysis combines towns and semi dense areas with rural areas because the marginal difference in remote work between the two categories is minimal (cf. the fourth section).

20 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.

trends in and out of cities (Burgalassi and 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

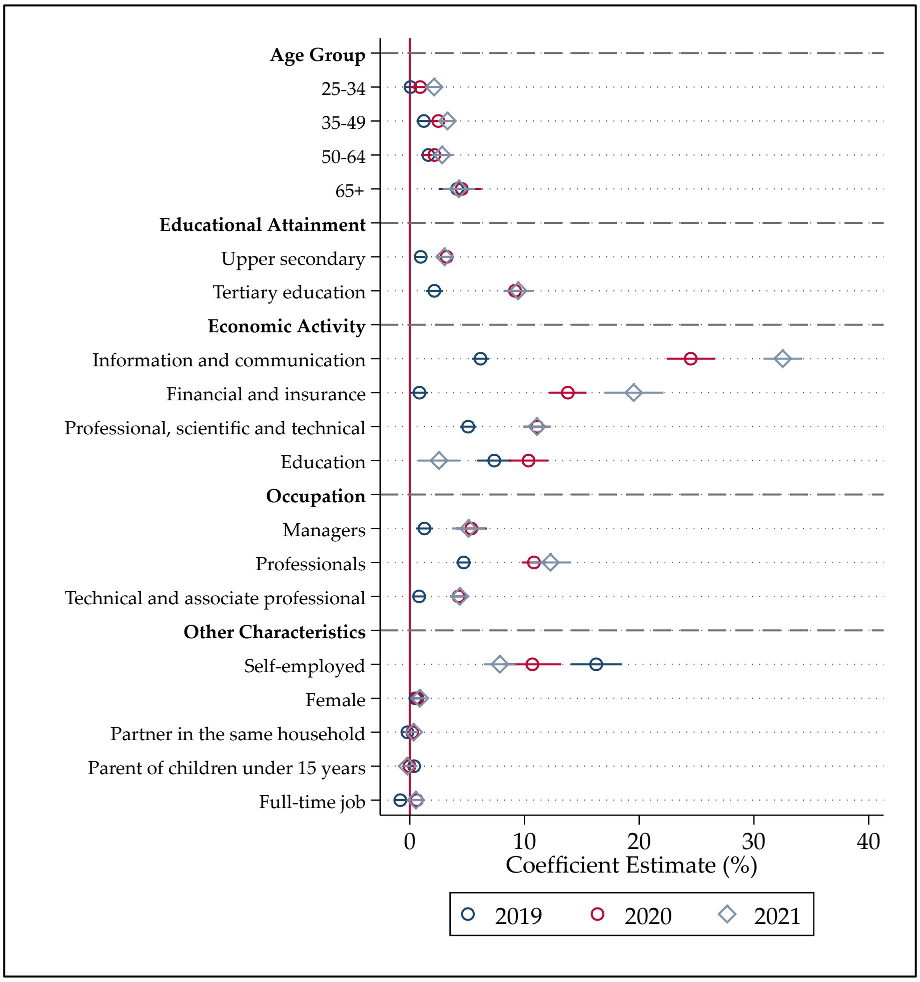
Figure 5.1 reports the regression coefficients and their 95% confidence intervals from a parsimonious specification of Equation 1, where the degree of urbanisation and the two regional indicators are not included, i.e., exclusively controlling for the composition hypothesis. The figure presents separate 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 Annex Table 6. 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 are preferrable for easier readability.

The findings can be summarised as follows. First, respondents belonging to older age groups are significantly more likely to work remotely.[21] 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.[22] 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. 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.

21 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 see such urban-rural divide (see appendix Table F.2).
22 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).

Figure 5.1. 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 Annex Table 6.
Source: own elaboration on data from the European Union Labour Force Survey (EU-LFS).

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. Relatedly, even holding age, sectors and occupations constant, tertiary education remains a strong and significant predictor of remote work.

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.[23] Results not presented but available on request suggest that the coefficient for identifying as a female respondent in 2020 and 2021 is 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 results by Sostero et al. (2020[20]), who have shown how the incidence of remote work by gender was similar across the EU, and by Garrote Sanchez et al. (2021[19]), who argue that gender has overall a limited power in explaining teleworkability around the world.

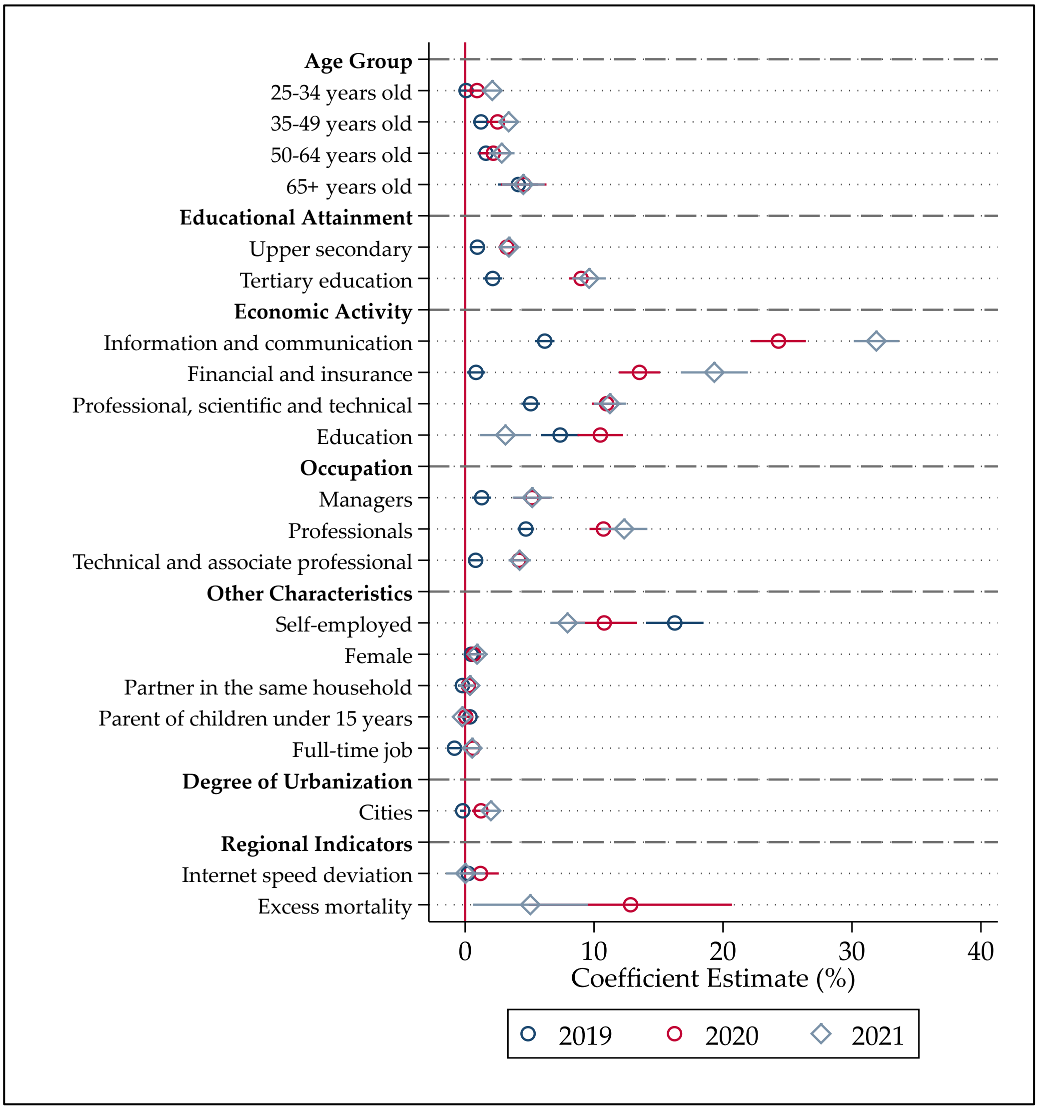
Figure 5.2 then reports the results from estimating a full specification of Equation (1), that is, controlling for the city dummy and the two regional regressors. The coefficients for all the other individual regressors remain nearly unchanged compared to Figure 5.2, either before or during the pandemic. 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.

In 2020, the coefficient for regional excess mortality, which serves as a measure for the severity of the pandemic, is notably high, positive, and statistically significant. This significance holds even when accounting for individual characteristics. With the inclusion of regional fixed-effects, the coefficient indicates a positive correlation between regional excess mortality in a particular month and the likelihood of individuals in that region engaging in remote work compared to other time periods. However, it is important to note that this association becomes less pronounced and loses both its magnitude and significance in 2021. This suggests that, following the initial impact of the pandemic, the decision of respondents to work remotely has become influenced by additional factors.

Similarly, the coefficient for the internet speed deviation is close to zero in 2019. It then became positive and significant in 2020 before reducing again in magnitude and significance in 2021. It should be recalled that internet speed is measured separately for cities, towns and semi-dense areas and rural areas in each region. Given the inclusion of regional fixed effects, it hence captures the role of having faster internet on the remote work probability of workers relative to others in the same region. Therefore, the results suggest that – pre-pandemic – the choice to work remotely was primarily linked to other factors. The local internet speed becomes a significant predictor during the first phase of the pandemic when individuals worked from home. In terms of size, the magnitude is comparable to the coefficient obtained for respondents aged 65+, or around half of that for tertiary education. Taken together, while a reliable internet connection is a precondition to work remotely, these findings may suggest that its presence per se is not a main driver of remote jobs, at least when comparing workers living in the same region.

[23] The analysis focuses only on individuals employed during the period of analysis. If women were more likely to drop out from the labour force or move to unemployment during this period, this might explain partially the lack of significant effects.

Figure 5.2. Who was more likely to work remotely and where?

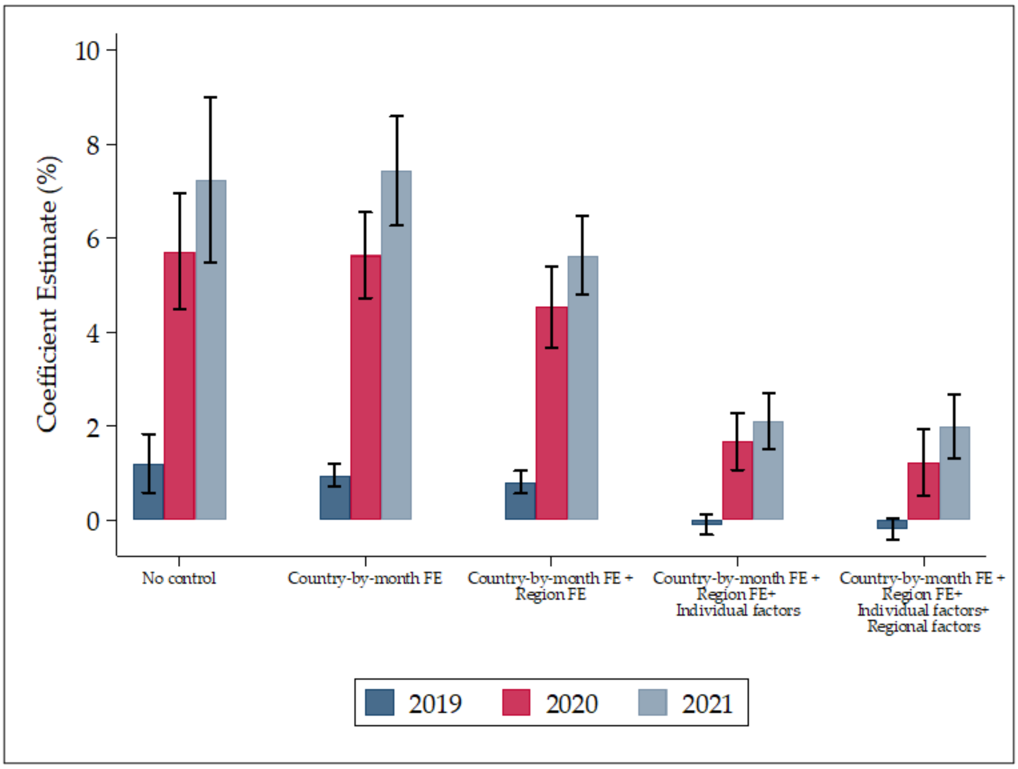


Note: This figure plots coefficient estimates and 95% confidence intervals on various individual and regional factors underlying remote work uptake. All regressions control for country-by-month and region-fixed effects. Robust standard errors are clustered at the TL2 level. Coefficient estimates and robust standard errors are also reported in Column (2) and (6) of Annex Table 6.
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 explain the correlation between working remotely and the city dummy.

Figure 5.3. 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.

The largest increase in the models' explanatory power occurs when including the individual regressors. Figure 5.3 presents the results from five model specifications. Each of them regresses $RemoteWork_{ir}$ on $City_{ir}$, while sequentially including the other sets of individual-level and regional 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). 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. Annex Table 8 reports the adjusted R^2s of the regressions underlying the results presented in Figure 5.3.

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.[24]

24 The method builds on the Kitagawa-Oaxaca-Blinder decomposition. See Gelbach (2016[10]) for more details.

Table 5.1. Is the gap in remote work between cities and other areas explained by individual or regional factors?

	Specification		Difference between the two specifications	% Share of column 3 explained by each set of factors
	Base (1)	Full (2)	(3)	(4)
Panel A: 2019				
City dummy (i.e., gap between cities and other areas, % points)	0.844***	-0.189*	1.033***	
	(0.130)	(0.113)	(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***	1.226***	3.525***	
	(0.462)	(0.359)	(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***	1.994***	3.542***	
	(0.438)	(0.346)	(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.

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 5.1 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 5.3.

Importantly, in 2019, individual factors explain 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 regional factors explain higher shares of the urban-rural remote work uptake gap, individual factors can still explain 87.6%. In 2021, the contribution of individual factors even reaches 99.7%. Together, it is possible to conclude that the urban-rural gap in remote work uptake is primarily driven by composition effects.

Conclusions

In 2020, the COVID-19 pandemic forced millions of employers and employees to adopt new forms of hybrid and flexible work. While remote work was introduced as a short-term solution to the lockdown measures imposed at the height of the pandemic, it will likely remain part of the work culture going forward. Addressing an existing gap in the scientific and policy literature, this paper explores the geography of actual remote work since the onset of the COVID-19 pandemic.

The paper makes three main contributions. First, it complements the existing evidence on Europe's remote work *potential* by developing a new measure of *actual* remote work. The paper provides the first systematic exploration of the new geography of remote work that has emerged across 30 European countries and shows how the expansion of remote work has been markedly uneven. Second, the analysis identifies the factors that explain such heterogeneity by testing the extent to which the individual likelihood of working remotely is explained by individual level characteristics (e.g., age, gender and family structure, educational attainments, sector/occupation of work, etc.) or by territorial determinants (such as internet speed and local severity of the pandemic). Third, the paper identifies what is the relative role of composition vs contextual factors in explaining the gap in remote work uptake observed between cities and other areas.

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 work, its uptake has been strongest in cities and capital regions. This finding is in line with recent theories on the effect of remote work on the future of cities. Bond-Smith and McCann (2022[28]) provide a theoretical explanation of why most remote workers may prefer to be located in or around large cities and highlight how the fall in commuting frequency associated to remote work counterintuitively favour larger urban areas where commuting distances are longer.[25]

The results also show that the uneven expansion of remote work 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. By contrast, gender, relationship status, and being a parent of children under 15 are not significantly associated with actual remote work uptake. This unexpected finding is in line with recent similar findings by Garrote Sanchez et al. (2021[19]) and cc

Regional factors such as internet speed and regional excess mortality are positively associated with remote work uptake 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

25 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 often not available outside of urban areas.

attributes. Similarly, the remote work gap between cities and other areas is also primarily driven by composition effects i.e., by the uneven distribution of workers with different characteristics.

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. A strength of this paper lies in its broad geographical coverage, including 30 countries. However, this comes at a cost as the EU-LFS dataset used for the analysis is not a panel. The absence of panel data allowing to follow the same workers over time makes it challenging to establish causal relationships between remote work and its potential enablers/inhibitors. Future research may focus on country-specific datasets allowing the adoption of more rigorous identification strategies. Furthermore, it is still early to assess the extent to which workers and employers will revert to pre-covid working habits after 2020 and 2021. Future research may focus on this key aspect.

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. In particular, because of data availability the current research is only able to focus on the height of the pandemic. While many commentators highlight how remote work is here to stay (Aksoy et al., 2022[29]) 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.

The findings of the study shed light on how the pandemic has influenced remote work in Europe, impacting cities and regions differently. Understanding this new remote work landscape is crucial for policymakers, directly affecting regional inequality and development. In recent decades many rural regions across OECD countries have faced higher population decline and aging than cities, as well as lower growth in living standards. The possibility to work remotely has been seen as a new opportunity for areas outside of large urban agglomerations to mitigate/reverse these structural trends (OECD, 2021[17]). For example, there has been a flourishing of initiatives aimed at offering co-working spaces and other support services for remote workers willing to move to rural areas and peripheral regions. The 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. Confirming studies from the US (Ramani and Bloom, 2021[30]; Ahrend et al., 2022[31]), this suggests that 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.

Considering these trends, 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, 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.

Finally, these results revealed challenges related to the ability of some workers to adopt remote working. Recognizing the changing nature of work, and the preference of most workers for more workplace flexibility (Aksoy et al., 2022[29]), policymakers should invest in 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.

References

Adams-Prassl, A. et al. (2022), "Work that can be done from home: evidence on variation within and across occupations and industries", *Labour Economics*, Vol. 74, p. 102083, https://doi.org/10.1016/j.labeco.2021.102083. [18]

Adrjan, P. et al. (2023), "Unlocked Potential: Work-from-Home Job Postings in 20 OECD Countries", *AEA Papers and Proceedings*, Vol. 113, pp. 604-608, https://doi.org/10.1257/pandp.20231014. [15]

Adrjan, P. et al. (2021), "Will it stay or will it go? Analysing developments in telework during COVID-19 using online job postings data", *OECD Productivity Working Papers*, No. 30, OECD Publishing, Paris, https://doi.org/10.1787/aed3816e-en. [14]

Ahrend, R. et al. (2022), "Changes in the geography housing demand after the onset of COVID-19: First results from large metropolitan areas in 13 OECD countries", *OECD Economics Department Working Papers*, No. 1713, OECD Publishing, Paris, https://doi.org/10.1787/9a99131f-en. [31]

Aksoy, C. et al. (2022), *Working from Home Around the World*, National Bureau of Economic Research, Cambridge, MA, https://doi.org/10.3386/w30446. [29]

Althoff, L. et al. (2022), "The Geography of Remote Work", *Regional Science and Urban Economics*, Vol. 93, p. 103770, https://doi.org/10.1016/j.regsciurbeco.2022.103770. [3]

Bond-Smith, S. and P. McCann (2022), "The work-from-home revolution and the performance of cities", *The Productivity Institute Working Paper Series* 26. [28]

Criscuolo, C. et al. (2021), "The role of telework for productivity during and post-COVID-19: Results from an OECD survey among managers and workers", *OECD Productivity Working Papers*, No. 31, OECD Publishing, Paris, https://doi.org/10.1787/7fe47de2-en. [16]

Cuerdo-Vilches, T., M. Navas-Martín and I. Oteiza (2021), "Working from Home: Is Our Housing Ready?", *International Journal of Environmental Research and Public Health*, Vol. 18/14, p. 7329, https://doi.org/10.3390/ijerph18147329. [25]

de Vos, D. et al. (2020), "Does broadband internet allow cities to 'borrow size'? Evidence from the Swedish labour market", *Regional Studies*, Vol. 54/9, pp. 1175-1186, https://doi.org/10.1080/00343404.2019.1699238. [21]

Diaz Ramirez, M., P. Veneri and A. Lembcke (2021), "Where did it hit harder?: The geography of excess mortality during the COVID-19 pandemic", *OECD Regional Development Papers*, No. 21, OECD Publishing, Paris, https://doi.org/10.1787/ab4848a4-en. [26]

Dingel, J. and B. Neiman (2020), “How many jobs can be done at home?”, *Journal of Public Economics*, Vol. 189, p. 104235, https://doi.org/10.1016/j.jpubeco.2020.104235. [8]

Eurofound (2020), “Living, Working and COVID-19”, *Publications Office of the European Union*. [7]

Fiorentino, S. et al. (2022), “The future of the corporate office? Emerging trends in the post-Covid city”, *Cambridge Journal of Regions, Economy and Society*, Vol. 15/3, pp. 597-614, https://doi.org/10.1093/cjres/rsac027. [6]

Florida, R., A. Rodríguez-Pose and M. Storper (2021), “Critical Commentary: Cities in a post-COVID world”, *Urban Studies*, Vol. 60/8, pp. 1509-1531, https://doi.org/10.1177/00420980211018072. [2]

Garrote Sanchez, D. et al. (2021), “Who on Earth Can Work from Home?”, *The World Bank Research Observer*, Vol. 36/1, pp. 67-100, https://doi.org/10.1093/wbro/lkab002. [19]

Gelbach, J. (2016), “When Do Covariates Matter? And Which Ones, and How Much?”, *Journal of Labor Economics*, Vol. 34/2, pp. 509-543, https://doi.org/10.1086/683668. [10]

Glaeser, E. (2021), “Urban resilience”, *Urban Studies*, Vol. 59/1, pp. 3-35, https://doi.org/10.1177/00420980211052230. [4]

Gottlieb, C. et al. (2021), “Working from home in developing countries”, *European Economic Review*, Vol. 133, p. 103679, https://doi.org/10.1016/j.euroecorev.2021.103679. [13]

Grabner, S. and A. Tsvetkova (2022), “Urban labour market resilience during the Covid-19 pandemic: what is the promise of teleworking?”, *Regional Studies*, pp. 1-16, https://doi.org/10.1080/00343404.2022.2042470. [5]

Hale, T. et al. (2021), “Variation in Government Response to COVID-19”, *Blavatnik School of Government Working Paper*. [27]

ILO (2020), *COVID-19: Guidance for Labour Statistics Data Collection: Defining and Measuring Remote Work, Telework, Work at Home and Home-Based Work*. [11]

Nathan, M. and H. Overman (2020), “Will coronavirus cause a big city exodus?”, *Environment and Planning B: Urban Analytics and City Science*, Vol. 47/9, pp. 1537-1542, https://doi.org/10.1177/2399808320971910. [1]

OECD (2023), *OECD Regional Outlook 2023: The Longstanding Geography of Inequalities*, OECD Publishing, Paris, https://doi.org/10.1787/92cd40a0-en. [24]

OECD (2022), *OECD Regions and Cities at a Glance 2022*, OECD Publishing, Paris, https://doi.org/10.1787/14108660-en. [23]

OECD (2021), *Implications of Remote Working Adoption on Place Based Policies: A Focus on G7 Countries*, OECD Regional Development Studies, OECD Publishing, Paris, https://doi.org/10.1787/b12f6b85-en. [17]

OECD (2020), “Capacity for remote working can affect lockdown costs differently across places”, *OECD Policy Responses to Coronavirus*. [9]

Ramani, A. and N. Bloom (2021), *The Donut Effect of Covid-19 on Cities*, National Bureau of Economic Research, Cambridge, MA, https://doi.org/10.3386/w28876. [30]

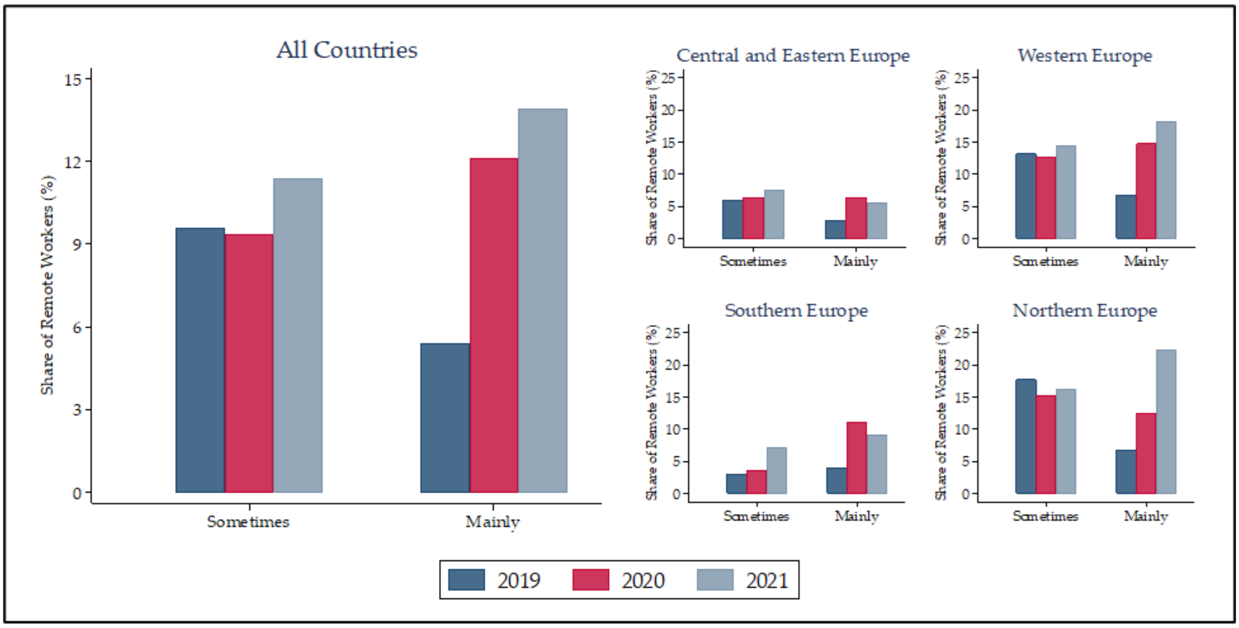
Sostero, M. et al. (2020), “Teleworkability and the COVID-19 Crisis: A new digital divide?”, *JRC Working Paper Series on Labour, Education and Technology* 5. [20]

Vilhelmson, B. and E. Thulin (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: Economy and Space*, Vol. 33/6, pp. 1015-1029, https://doi.org/10.1068/a33207. [22]

Yang, L. et al. (2021), “The effects of remote work on collaboration among information workers”, *Nature Human Behaviour*, Vol. 6/1, pp. 43-54, https://doi.org/10.1038/s41562-021-01196-4. [12]

Annex A. Shares of remote workers by country

Annex Figure 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 3.1). 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).

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

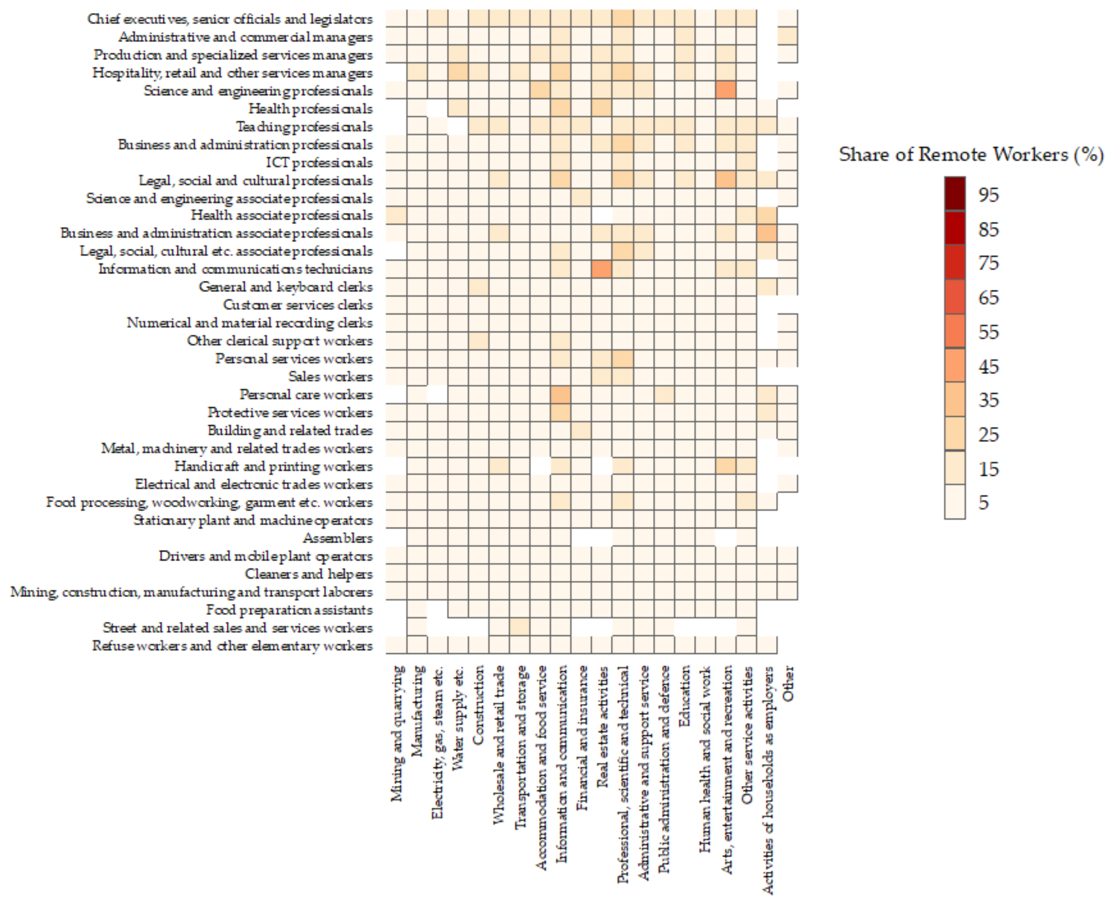
Note: This figure plots shares of remote workers by remote work frequency for 30 European countries in 2019 to 2021. It shows that for most countries, shares of workers who "mainly" worked remotely increased significantly whereas shares of workers who "sometimes" worked remotely varied little.
Source: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

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

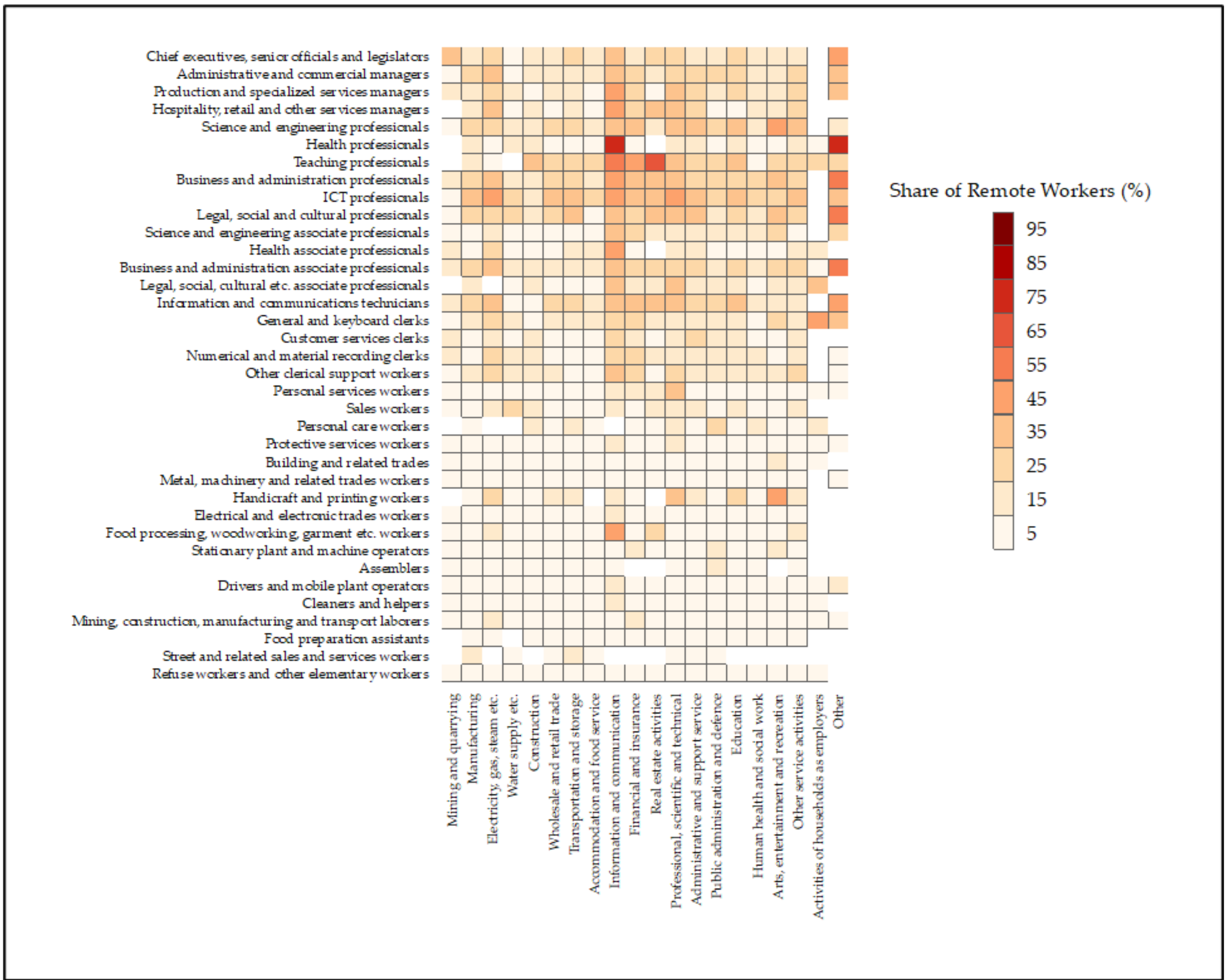
Note: This figure plots the monthly shares of remote workers and an overall index measuring the stringency of government policy responses to COVID-19 from 2019 to late 2021. It shows that, across most countries, the shares of remote workers closely followed the stringency index.
Source: European Union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

Annex Figure 4 . Heatmaps of remote work shares for industry-occupation pairs, 2019 to 2021

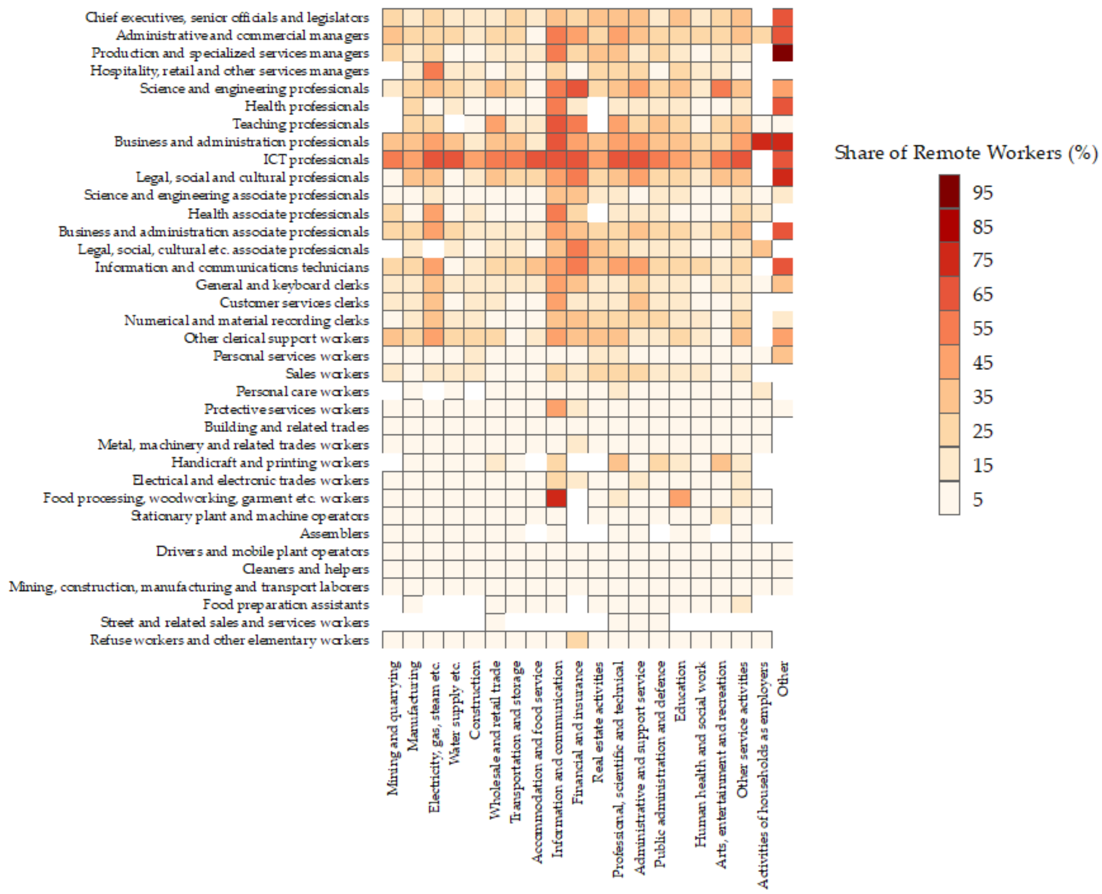
Panel A: 2019



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).

Annex B. The measurement of remote work potential and its correlation to actual remote work uptake

The paper follows the approach by Dingel & Neiman (2020[8]) 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.[26] 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[8]), 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.[27] 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[8]) 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 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.

26 The version of SOC is the SOC 2010.
27 The version of ISOC is the ISOC-08.

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.

Annex Table 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[8]) 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[8]).
Source: Dingel & Neiman (2020[8])

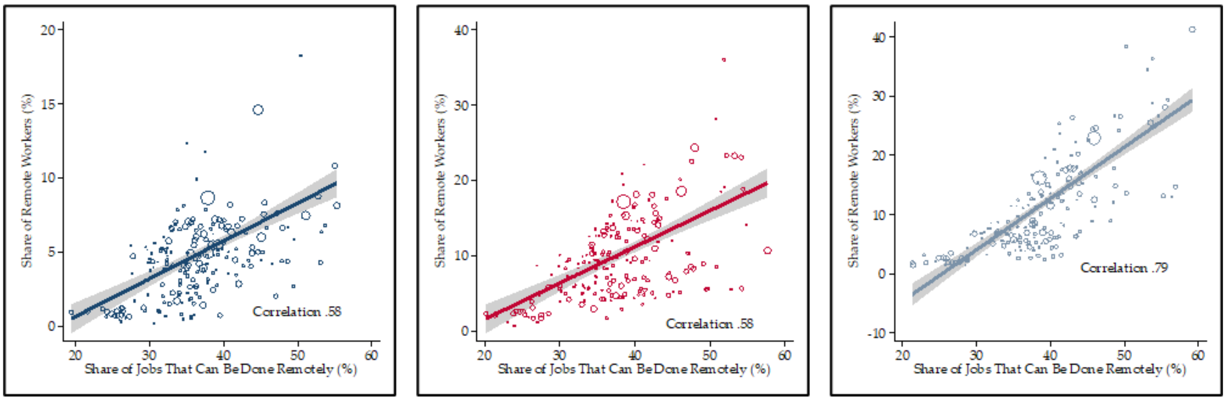
Annex C. The correlation between potential and actual remote work

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[8]) and discussed in Appendix Annex 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.

Annex Table 2 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.

Annex Table 2. 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).

Annex D. Descriptive statistics

Annex Table 3. Descriptive statistics for key individual variables from the EU-LFS

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	196	192	4
Towns and semi-dense areas	-5.940	1.698			
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	200	196	4
Towns and semi-dense areas	-6.738	1.657			
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	197	193	4
Towns and semi-dense areas	-8.000	1.529			
Rural areas	-24.744	1.679			

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).

Annex Table 4. 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	196	192	4
Towns and semi-dense areas	-5.940	1.698			
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	200	196	4
Towns and semi-dense areas	-6.738	1.657			
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	197	193	4
Towns and semi-dense areas	-8.000	1.529			
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 which are matched at the TL1 level due to data availability. Data on excess mortality for Cyprus and Ireland are missing. 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 Diaz Ramirez et al., (2021[26]).

Annex E. Potential changes in demographic composition between cities and other areas

Annex Table 5 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.

Annex Table 5. 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).

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.

Annex F. Regression results

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

OLS regression results underlying Figure 5.1 and Figure 5.2 and Logit regression results

	2019				2020				2021			
Variable	OLS	OLS	Logit	Logit	OLS	OLS	Logit	Logit	OLS	OLS	Logit	Logit
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Age group												
[1] 25-34 years old	0.001 (0.002)	0.001 (0.002)	0.354*** (0.056)	0.356*** (0.056)	0.009** (0.004)	0.009** (0.004)	0.211*** (0.076)	0.207*** (0.077)	0.021*** (0.003)	0.021*** (0.003)	0.313*** (0.035)	0.303*** (0.037)
[2] 35-49 years old	0.012*** (0.003)	0.012*** (0.003)	0.671*** (0.066)	0.671*** (0.066)	0.025*** (0.004)	0.025*** (0.004)	0.385*** (0.079)	0.383*** (0.080)	0.033*** (0.004)	0.034*** (0.004)	0.453*** (0.046)	0.456*** (0.049)
[3] 50-64 years old	0.016*** (0.003)	0.016*** (0.003)	0.746*** (0.062)	0.745*** (0.062)	0.021*** (0.006)	0.022*** (0.006)	0.347*** (0.100)	0.348*** (0.099)	0.028*** (0.005)	0.028*** (0.005)	0.392*** (0.066)	0.391*** (0.069)
[4] 65+ years old	0.041*** (0.008)	0.041*** (0.008)	0.989*** (0.085)	0.987*** (0.086)	0.045*** (0.009)	0.046*** (0.009)	0.566*** (0.115)	0.564*** (0.116)	0.043*** (0.007)	0.045*** (0.008)	0.529*** (0.082)	0.539*** (0.092)
Educational Attainment												
[5] Upper secondary	0.010*** (0.002)	0.009*** (0.002)	0.275*** (0.052)	0.274*** (0.052)	0.032*** (0.003)	0.032*** (0.003)	0.663*** (0.079)	0.667*** (0.078)	0.030*** (0.003)	0.034*** (0.003)	0.665*** (0.062)	0.691*** (0.066)
[6] Tertiary education	0.021*** (0.004)	0.021*** (0.004)	0.535*** (0.067)	0.532*** (0.068)	0.092*** (0.005)	0.090*** (0.005)	1.293*** (0.083)	1.273*** (0.082)	0.094*** (0.006)	0.096*** (0.007)	1.300*** (0.066)	1.302*** (0.071)
Economic Activity												
[7] Information and communication	0.062*** (0.004)	0.062*** (0.004)	0.983*** (0.068)	0.983*** (0.067)	0.245*** (0.011)	0.243*** (0.011)	1.588*** (0.067)	1.571*** (0.068)	0.325*** (0.008)	0.319*** (0.009)	1.882*** (0.050)	1.835*** (0.050)
[8] Financial and insurance	0.008*** (0.004)	0.008** (0.004)	0.282*** (0.087)	0.281*** (0.086)	0.138*** (0.008)	0.135*** (0.008)	1.075*** (0.054)	1.057*** (0.054)	0.195*** (0.013)	0.193*** (0.013)	1.322*** (0.044)	1.301*** (0.043)
[9] Professional, scientific and technical	0.051*** (0.004)	0.051*** (0.004)	0.563*** (0.041)	0.563*** (0.040)	0.111*** (0.006)	0.110*** (0.006)	0.735*** (0.042)	0.720*** (0.042)	0.111*** (0.006)	0.112*** (0.006)	0.723*** (0.030)	0.717*** (0.028)
[10] Education	0.074*** (0.008)	0.074*** (0.008)	1.219*** (0.123)	1.219*** (0.123)	0.104*** (0.009)	0.105*** (0.009)	0.854*** (0.071)	0.865*** (0.073)	0.025*** (0.009)	0.031*** (0.010)	0.296*** (0.073)	0.332*** (0.078)

Occupation												
[11] Managers	0.013*** (0.004)	0.013*** (0.004)	0.532*** (0.066)	0.533*** (0.066)	0.054*** (0.007)	0.052*** (0.007)	0.768*** (0.053)	0.754*** (0.055)	0.051*** (0.007)	0.052*** (0.008)	0.721*** (0.052)	0.723*** (0.054)
[12] Professionals	0.047*** (0.003)	0.047*** (0.003)	0.846*** (0.041)	0.847*** (0.041)	0.108*** (0.005)	0.107*** (0.005)	1.025*** (0.037)	1.014*** (0.037)	0.123*** (0.009)	0.123*** (0.009)	1.094*** (0.043)	1.084*** (0.044)
[13] Technical and associate professional	0.008*** (0.003)	0.008*** (0.003)	0.388*** (0.075)	0.388*** (0.075)	0.043*** (0.004)	0.042*** (0.004)	0.681*** (0.041)	0.674*** (0.042)	0.044*** (0.004)	0.042*** (0.004)	0.682*** (0.034)	0.664*** (0.035)
Other Characteristics												
[14] Self-employed	0.162*** (0.011)	0.163*** (0.011)	2.146*** (0.044)	2.147*** (0.044)	0.107*** (0.013)	0.108*** (0.013)	0.951*** (0.081)	0.962*** (0.081)	0.079*** (0.007)	0.079*** (0.007)	0.704*** (0.058)	0.701*** (0.059)
[15] Female	0.005*** (0.002)	0.005*** (0.002)	0.181*** (0.041)	0.181*** (0.041)	0.007*** (0.002)	0.007*** (0.002)	0.147*** (0.021)	0.148*** (0.021)	0.009*** (0.003)	0.009*** (0.003)	0.163*** (0.024)	0.171*** (0.026)
[16] Partner in the same household	-0.002 (0.002)	-0.002 (0.002)	-0.037 (0.025)	-0.038 (0.025)	-0.001 (0.002)	0.003 (0.002)	0.032* (0.017)	0.040** (0.018)	0.003* (0.002)	0.004* (0.002)	0.027* (0.016)	0.039** (0.017)
[17] Parent of children under 15	0.004*** (0.001)	0.004*** (0.001)	0.065*** (0.025)	0.065*** (0.025)	-0.000 (0.002)	0.000 (0.002)	-0.009 (0.022)	0.001 (0.023)	-0.002 (0.002)	-0.002 (0.002)	-0.034* (0.018)	-0.033 (0.020)
[18] Full-time job	-0.008*** (0.002)	-0.008*** (0.002)	-0.125*** (0.048)	-0.125*** (0.048)	0.006*** (0.002)	0.006*** (0.002)	0.065*** (0.024)	0.065*** (0.024)	0.005 (0.004)	0.005 (0.004)	0.036 (0.034)	0.036 (0.034)
Degree of Urbanisation												
[19] Cities		-0.002* (0.001)		-0.036 (0.026)		0.012*** (0.004)		0.164*** (0.031)		0.020*** (0.003)		0.220*** (0.022)
Regional Indicators												
[20] Internet speed deviation		-0.002 (0.002)		0.073 (0.046)		0.012* (0.007)		0.138** (0.051)		0.000 (0.008)		0.148** (0.059)
[21] Excess Mortality						0.128*** (0.040)		0.537** (0.247)		0.051** (0.023)		0.487** (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.

Annex Table 7. Remote work uptake across age groups, by degree of urbanisation and gender

	2019 (1)	2020 (2)	2021 (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).

Annex 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 5.3. Overall, Model 5 allows explaining around 18.0% of the variation in individual remote work uptake. Confirming the findings highlighted in Figure 5.3, the largest increase in the explanatory power of the model occurs when including the individual regressors.

Annex Table 8. Explaining the gap in remote work uptake between cities and other areas

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 5.3. 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.