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# On Working from Home in European Countries



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# On Working from Home in European Countries

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## Abstract

**Purpose**

We analyze the evolution of working from home (WFH) within industries in 12 European countries in the period 2008-2017 and study its relationship with information and communication technologies (ICT).

**Design/methodology/approach**

We use data from the EU-LFS to document the trends and levels of WFH within industries in 12 European countries. We further use the EU-KLEMS database and a difference-in-difference approach to study whether the fall in prices of ICT is associated with a higher share of employees who work from home in industries that depend more on ICT relative to industries that depend less.

**Findings**

We show that WFH has increased almost everywhere and that there is significant heterogeneity across industries. We provide evidence that the fall in prices of ICT is associated with a higher share of employees who work from home in industries that depend more on ICT relative to industries that depend less. This result also holds within age, gender, and occupation groups. While we find no significant differences among gender and occupation groups, the positive association between the fall in ICT prices and WFH increases with age.

**Originality**

This paper has two main contributions. First, it reports that WFH has increased in European countries in the period 2008-2017. Second, it provides new explorations about the relationship between ICT and WFH by using the price variation of ICT.



**Keywords:** Working from Home; ICT; Age; Gender; Occupation Groups

**JEL classification:** J23; J24; O33

# 1 Introduction

Working from home (WFH) has recently gained importance and prevalence because of the COVID-19 pandemic and lockdown policies. It can be associated with changes in the locations of work and demand for services in those locations, fall in commuting time, more flexible types of work, and lower infection rates during pandemics/epidemics (e.g., Brotherhood and Jerbashian, 2023, Edwards and Field-Hendrey, 2002, Gaspar and Glaeser, 1998).

Nevertheless, WFH is not a new phenomenon. Using data from the representative EU Labour Force Survey (EU-LFS), we provide evidence that the share of employees who work from home has increased steadily in the period 2008-2017 in all industries of most European countries. WFH has also increased within age, gender, and occupation groups. We explore the relationship between the steady and ubiquitous rise in WFH in 2008-2017 and the rise in information and communication technologies (ICT) use. Our results show that WFH has increased more in industries that depend more on ICT than in those industries that depend less on ICT. We further utilize a difference-in-differences framework in the spirit of Rajan and Zingales (1998) and show that WFH has increased more in industries that depend more on ICT in countries where ICT prices have declined more as compared to countries where ICT prices have declined less. Taken together, these findings provide support for the hypothesis that ICT facilitates and increases WFH (e.g., Autor, 2001, Oettinger, 2011). These technologies include computers and the Internet. In particular, there have been important advances in high-speed Internet, cloud computing, video conferencing tools, and collaboration software during the period of study that are especially relevant in facilitating WFH (e.g., Byrne, Corrado, and Sichel, 2018, European Commission, 2013, Gruber, Hätönen, and Koutroumpis, 2014).

In our analysis, we distinguish between three age groups: young (younger than 30), medium-age (between 30 and 45), and old (older than 45). We also split occupations into high- and low-wage groups motivated by the evidence that information technologies complement high-wage occupations (e.g., Autor, Levy, and Murnane, 2003, Acemoglu and Autor, 2011, Jerbashian, 2019). The result that WFH has increased with the fall in ICT prices holds within age, gender, and occupation groups. Moreover, we find that the effect of the fall in ICT prices on the share of individuals who work from home is not statistically different across gender and occupation groups. However, there are statistically significant and economically meaningful differences across age groups. WFH has increased more among the old than among the young with the fall in ICT prices. All these results are robust to a wide range of specification checks and alternative identifying assumptions.

A few earlier papers have studied alternative work arrangements and, in particular, WFH. Edwards and Field-Hendrey (2002) emphasize the importance of WFH for women. Mas and Pallais (2017) and Maestas, Mullen, Powell, Wachter, and Wenger (2018) use a discrete choice experiment and stated-preference analysis and estimate that job applicants and employees are willing to accept lower wages for the opportunity to work from home. Mas and Pallais (2020) offer a review of the literature on workers' preferences for alternative work arrangements, such as WFH, with a focus on the US. According to Bloom, Kretschmer, and Van Reenen (2009), the result that employees are willing to accept lower wages for WFH can hold because WFH can improve work-life balance. WFH can also be associated with increased productivity according to Bloom, Liang, Roberts, and Ying (2015), and ICT can help with informational and relational needs when employees work from home (Lee, 2023). In turn, Oettinger (2011) and Mateyka, Rapino, and Landivar (2012) document that WFH has steadily increased in the US during the past two decades. Oettinger (2011) also offers evidence showing that WFH has increased more in occupations that use ICT more intensively. Ollo-López, Goñi-Legaz, and Erro-Garcés (2021) also document a positive country-level association between telework and ICT. Our results complement these results and contribute to these studies by showing that the fall in ICT prices is associated with a higher increase in WFH in industries that depend more on ICT than in industries that depend less on ICT.

The measurement and analysis of WFH have gained particular importance recently because of the COVID-19 pandemic.[1] Dingel and Neiman (2020) propose a task-based

[1]The results of Brotherhood and Jerbashian (2023) suggest that WFH can lead to lower losses in output and employment and fewer infections and deaths during pandemics such as the COVID-19.

method, which relies on determining tasks that are incompatible with WFH, and evaluate the WFH capacity in the United States (similar approach has been used for example by Gottlieb, Grobovšek, Poschke, and Saltiel, 2021). There tend to be sizable differences in predictions regarding WFH capacity across studies utilizing such methods because of data limitations and differences in judgments regarding job characteristics that can be compatible with WFH. Nevertheless, the results of Alipour, Falck, and Schüller (2020) suggest that these task-based methods can relatively accurately capture relevant variation in WFH capacity when direct measures are not readily available. In turn, several studies have used data from surveys and administrative employment statistics to measure the actual and potential WFH capacity (e.g., Adams-Prassl, Boneva, Golin, and Rauh, 2022, Alipour et al., 2020). These studies document significant differences in WFH across industries and occupations (see also Aksoy, Barrero, Bloom, Davis, Dolls, and Zarate, 2022, Criscuolo, Gal, Leidecker, Losma, and Nicoletti, 2021, for two recent surveys on WFH). In turn, Barrero, Bloom, and Davis (2021) and Jerbashian and Vilalta-Bufí (2022) show that WFH has significantly increased during the pandemic. Barrero et al. (2021) further argue that WFH will stay high after the pandemic. We contribute to these papers by showing that there were significant positive trends in WFH before the pandemic in European countries. Our uncovered association between ICT and WFH also suggests that the capacity of WFH in countries depends on the availability and use of ICT in addition to the structure of employment as emphasized by recent studies.[2]

These results also contribute to the literature that studies the economic impact of ICT and, in particular, the effect of ICT on labor demand and employment (e.g., Krueger, 1993). This literature shows that ICT and technological progress in it has had an important impact on the economy and growth (e.g., Jensen, 2007, Stiroh, 2002). ICT prices have significantly fallen over several decades, and its adoption and use have increased. The fall in ICT prices, for example, has increased the demand for abstract task-intensive occupations and has reduced the demand for routine-task-intensive occupations (e.g., Autor et al., 2003, Jerbashian, 2019). Jerbashian (2019) shows that the fall in ICT

[2]Evidence from several surveys suggests that businesses have invested in ICT to facilitate WFH during the COVID-19 pandemic (e.g., Barrero et al., 2021).

prices is also associated with a higher share of employment in abstract-task-intensive occupations among females than among males in industries that have a high ICT dependence.[3] Abstract tasks, such as data analysis and human resources management, tend to be easier to perform from home, especially with the recent advances in ICT, whereas routine tasks, such as assembly, tend to be hard to perform from home. In turn, Falck, Heimisch-Roecker, and Wiederhold (2020) show significant wage returns to ICT skills. Our results suggest that there can also be non-monetary returns to ICT skills, such as better opportunities to work from home.

The next section describes the data and our empirical methodology. Section 3 provides descriptive results, while section 4 summarizes the estimation results. Section 5 provides some robustness checks on the estimation results. The last section concludes.

## 2 Data and Empirical Methodology

We use data from 12 industries in 12 European countries for the period 2008 to 2017, excluding industries with potential large state involvement, such as the health and education sector, and industries with a small number of observations in the labor force survey.[4] We use data from 2008 onward because of industry classification changes in the EU Labour Force Survey (EU-LFS) database from NACE Rev. 1 to Rev. 2 in 2008. The period of analysis finishes in 2017 because the information on ICT prices from EU-KLEMS is not available for later years. The period under study is relevant as it comprises years where advances in ICT facilitated WFH. Moreover, it finishes before the COVID-19 pandemic when large non-market forces affected WFH.

The data for WFH are from the representative, individual-level EU-LFS. Individuals work from home when there is an agreement with the employer, and home-work-hours count as working time. This definition excludes WFH for personal reasons, due to time constraints, and without wage compensation, and highlights work flexibility agreed upon

[3]Beaudry, Doms, and Lewis (2010) show that firms and industries that use ICT intensively are also human capital-intensive in production.

[4]We exclude those industries with potential large state involvement to avoid incorporating changes in WFH that are not driven by market forces. We have nevertheless checked that our results are robust to their inclusion.

with the employer. The frequency of WFH is reported as "usually" if the respondent has worked at home for at least half of the working days in the reference period, "sometimes" if the respondent has worked at home for less than half of the working days, and "never" if the respondent has not worked at home during the reference period.[5] We compute the share of employed individuals who report that they work from home either sometimes or usually in each sample industry, country, and year, using the sample weights from the survey. Self-employed, family workers, and individuals who are older than 65 are excluded from the sample. Industries have 1-digit NACE Rev. 2 coding.

We also compute the share of employees who work from home within age, gender, and occupation groups using data from the EU-LFS database. Age groups are young (younger than 30), medium-age (between 30 and 45), and old (between 45 and 65), and occupations are split into high and low-wage groups. This division of occupations is motivated by research showing that ICT complements high-wage occupations (e.g., Autor et al., 2003, Acemoglu and Autor, 2011, Jerbashian, 2019). Moreover, the tasks usually performed in high-wage occupations, such as data analysis, are human capital-intensive and tend to be easier to perform from home than the usual tasks in the rest of the occupations (e.g., Dingel and Neiman, 2020). The classification of occupations changed from ISCO-88 to ISCO-08 in 2011, and this way of splitting occupations has the added convenience that it allows us to match these classifications. Occupations commanding high wages are Managers, Professionals and Technicians, and Associate Professionals and coincide in these classifications. We compute the share of employed individuals who report that they work from home at least sometimes in each of these categories.

The data for ICT are from the 2019 version of the EU KLEMS database (Adarov and Stehrer, 2019, Stehrer, Bykova, Jager, Reiter, and Schwarzhappel, 2019). These technologies include computing and communications equipment and computer software and databases. We use the share of ICT capital out of total capital to construct a proxy for industries' dependence on ICT. This proxy needs to identify the technological differences

[5]There is a variation in the design of the question for WFH and the coding of responses across countries in the EU-LFS. We discuss this in detail in the Online Appendix. We also perform robustness check exercises which show that this does not play an important role in our results.

across industries. We follow Rajan and Zingales (1998) and the literature motivated by their methodology and use data from US industries to accomplish this (e.g., Barone and Cingano, 2011). The measure for industries' dependence on ICT (ICT Dependence) is defined as the share of ICT capital in total capital in US industries averaged over the 2008-2017 period. Its variation is across industries. Panel $B$ of Table 1 reports the values of ICT Dependence across industries. The value of this measure is the largest in the Information and Communication and Financial and Insurance Activities industries. It is the lowest in the Real Estate and Agriculture, Forestry, and Fishing industries.

Other studies also measure industry ICT Dependence using US data (Rajan and Zingales, 1998, Barone and Cingano, 2011). There are several reasons for doing that. US markets are arguably the least regulated and the closest to the laissez-faire, and there is evidence that regulations matter for cross-country differences in ICT adoption (Jerbashian and Kochanova, 2016). Additionally, US industries are the world leaders in terms of investments in ICT and the level of ICT capital. Therefore, the confounding variation in the share of ICT capital in total capital because of temporary shocks and regulations is likely to be the smallest in US industries. To test this and the validity of this measure, we exploit time and industry variation in the share of ICT capital in total capital in US industries over the 2008-2017 period and the variation of the share of ICT capital in industries in the sample European countries. Although there have been large investments in ICT over this period, industry-level variation in the share of ICT capital in US industries accounts for nearly 100 percent of the total variation. Moreover, the share of ICT capital in US industries firmly correlates with the share of ICT capital in the industries of the sample European countries (see Panel $B$ in Table 1 and Table 2). These observations suggest that the dependence measure used in this paper is likely to identify the technological differences across industries but not temporary shocks.[6]

We also need a measure for the price of information technologies $p_{ICT}$. To construct it, we obtain the price of investments in information technologies in countries and years

[6]The measure of dependence used in this paper firmly correlates with similar measures used in the literature (see, e.g., Chen, Niebel, and Saam, 2016). We perform a range of robustness checks for it in Table 7.

in our sample from the EU KLEMS database. They are available till 2017 for all sample countries except Spain and Sweden. The data for Spain and Sweden are till 2016. We normalize the price of investments in information technologies with the price of investments in general physical capital and use it as a measure for the price of information technologies (ICT Price). Table 2 offers basic statistics for ICT Price in Panel $C$. ICT Price displays significant variation over time and across countries. The over-time variation can be largely attributed to the significant innovations in ICT that occurred over the sample years in the US and to the rise of ICT production in Asia and, in particular, in China. The country-level variation is likely to be stemming from regulations that affect the access to and adoption of ICT. Figure 2 illustrates the fall in ICT prices taking the average across sample countries.

We follow a difference-in-difference approach. Our empirical methodology is very similar to the one used by Rajan and Zingales (1998) and Jerbashian (2019).[7] The dependent variable in all our estimations is the share of employees in industry $i$, country $c$, and year $t$ who at least sometimes work from home. Our main specification is:

$$\begin{aligned} \text{WFH}_{i,c,t} &= \beta \Big[\text{Industry i's Dependence on ICT}_i \times (1/\text{ICT Price})_{c,t}\Big] \\ &\quad + \sum_c \sum_i \zeta_{c,i} + \sum_c \sum_t \xi_{c,t} + \eta_{i,c,t}, \end{aligned} \tag{1}$$

where $\zeta$ and $\xi$ are country-industry and country-year fixed effects respectively, and $\eta$ is an error term.

The parameter of interest is $\beta$. It captures the relationship between the fall in ICT prices and WFH. It is identified from the variation of ICT prices over time, the variation of ICT dependence across industries, and within country, time, and industry variation of the interaction term. We expect this coefficient to be positive, as we expect that WFH increases more with the fall in ICT prices in industries with higher ICT dependence than in industries with lower ICT dependence. We perform this estimation for each age, gender, and occupation group. We do not have *a priori* expectations about differences

[7] Our main specification and the measures of the variables closely follow the theoretical model presented in the Online Appendix.

across these groups.

This empirical methodology involves trade-offs. An advantage is that it can alleviate endogeneity concerns arising with the potentially omitted country- and industry-level variables with country-industry and country-year fixed effects. For example, these fixed effects control for labor market regulations and discriminatory practices potentially affecting WFH. Admittedly, however, this test might not fully reveal the effects of the fall in ICT prices on WFH if there are economy-wide changes in WFH stemming from the fall in ICT prices that are not different across industries. In such a case, this test can also be viewed as a test of whether significant industry-level differences exist.

## 3 Descriptive Results

This section describes the levels of WFH across industries and countries, its changes during 2008-2017, and its relationship with ICT Dependence. On average, WFH has increased by about four percentage points in the sample industries and countries in 2008-2017 (see Figure 1).

WFH and its change vary significantly across industries (see Table 1). Around 30% of workers in the Information and Communication Industry report that they work from home at least sometimes. About 17% of employees report that they work from home at least sometimes in the Financial and Insurance Activities and Real Estate industries. In contrast, less than 4% of workers report WFH in the Accommodation and Food Service industry. Barrero et al., 2021, report a similar ranking of industries using data from the US. The last column of Panel $A$ in Table 1 shows that, on average, WFH has increased in all industries during the sample period and that the levels of WFH are highly correlated with its changes.

The levels of WFH and its changes also vary across countries (see Panel $A$ of Table 2). WFH has increased almost everywhere. It has increased less in the Southern European countries than in the Northern European countries. An exception is Germany, where WFH has declined from 8.8 percent to 7.6 percent during the sample period.

Table 3 offers basic statistics for the WFH variable across different groups. Young workers tend to work significantly less from home than medium-age and old workers (see Panel *A*). This can be because of the stronger preference to work from home of older workers and learning opportunities during on-site work for younger workers (de Graaff and Rietveld, 2007, Sarbu, 2015). There are no significant differences in WFH between genders (see Panel *B*). The share of workers who report WFH at least sometimes is higher in high-wage occupations than in low-wage occupations (see Panel *C*). Oettinger (2011) presents a similar result using data from the US. This result reflects that the usual tasks in high-wage occupations, such as data analysis, are easier to perform at home than those in low-wage occupations. Importantly, WFH has increased in all these categories during the sample period, as shown in the last column of Table 3. The establishment of the trends in WFH as a stylized fact is one of the contributions of this paper.[8]

The value of ICT Dependence is highly correlated with the changes in WFH in sample industries (see Panel *A* of Table 1). This implies that the growth in WFH is stronger in industries that depend more on ICT. The last two columns of Panel *A* of Table 2 provide further evidence. We compute the average changes in WFH in industries above the median value of ICT Dependence (HD Industries) and in industries below the median value of ICT Dependence (LD Industries) in sample countries. WFH has increased more in industries with a high value of ICT Dependence than in industries with a low value of ICT Dependence in almost all countries. The exceptions are Denmark and Germany. In Denmark, it has increased slightly less in industries with a high value of ICT Dependence. In Germany, where it has slightly fallen during the sample years, it has done so less in industries with a high value of ICT Dependence as compared to industries with a low value of ICT Dependence.

[8]As reported in the Online Appendix, the pair-wise correlations of the WFH within groups are large, which supports the existence of a systematic pattern and the hypothesis that there is a technological cause for changes in the WFH. The Online Appendix also reports the results from the analysis of variance of the WFH measure and changes in WFH within groups in Germany.

# 4 Estimation Results

Panel $A$ of Table 4 reports the baseline estimate of $\beta$ from the specification (1) using our main sample. The coefficient is positive and significant. This implies that WFH increases with the fall in ICT prices and this increase is larger in industries that depend more on ICT than in industries that depend less on ICT.[9]

One way to quantify these results and show their economic significance is as follows. We compute

$$\hat{\beta} \times \Delta 1/\text{ICT Price} \times \Delta\text{ICT Dependence}, \tag{2}$$

where $\Delta 1$/ICT Price is measured as the average change in 1/ICT Price in the sample period, and $\Delta$ICT Dependence is the difference between the averaged values of ICT Dependence in industries where ICT Dependence is higher than its sample median and in industries where ICT Dependence is lower than its sample median. Panel $B$ of Table 4 reports the computed effect, and it is 0.017. We also compute the changes in WFH during the sample period in industries with higher than the median ICT Dependence and industries with lower than the median ICT Dependence and the difference between these changes, which is 0.032. This suggests that the fall in ICT prices has a strong effect on WFH and explains about 50 percent of the actual variation in the WFH variable corresponding to the empirical specification.[10]

We also estimate the specification (1) for each age, gender, and occupation group. Table 5 reports the results. The estimated coefficient is positive and significant in all cases and these results are broadly consistent with the main result reported in Panel $A$ of Table 4.

Panels $A - C$ of Table 5 report the results within age groups. According to the point estimates, the association between the fall in ICT prices and WFH is statistically significantly stronger among old individuals than among the young. The results for

[9]Our main result also holds when we use the share of employed individuals who report that they usually work from home as the measure of WFH. We provide a detailed discussion in the Online Appendix.

[10]The results in the Online Appendix report that country-level variation in ICT prices is as important as yearly and country-year-level variation. This suggests that there is room for policies that affect ICT prices.

the medium-age individuals are not statistically significantly different from the results for young and old individuals. An explanation for the differences across age groups is that the preference for working from home increases with age and the opportunities for productivity gains from working on-site decline with it. For example, young individuals usually reside in their parent's house in Europe. Young workers may also have greater opportunities to learn from their colleagues and improve their productivity while working on-site than old workers. In turn, old individuals are usually averse to commuting and travel which can amplify their willingness to work from home. Allen, Johnson, Kiburz, and Shockley (2013), Bal and Jansen (2016), de Graaff and Rietveld (2007) and Sarbu (2015), among others, corroborate these arguments.

We attempt to derive suggestive evidence regarding the role of preferences and check the differences across age groups among single and married employees. A rationale for such a test is that married young individuals are more likely to live in their own house, while single young individuals are more likely to live in their parents' house. Living in their own house might give them a stronger preference for WFH. In such a case, we expect that married young individuals behave similarly to old individuals, while single young individuals are less affected by the change in ICT prices as they are less willing to work from home. The results reported in Table 6 support this hypothesis. The association between the fall in ICT prices and WFH is stronger for single old individuals than for single young. In contrast, the association between the fall in ICT prices and WFH among married young individuals is not statistically significantly different from this association among married old individuals. When this indicates that preferences for WFH can play a role in the uncovered association among age groups, it is admittedly not conclusive. Data limitations do not allow us to explore this association further.

Panels *D* and *E* of Table 5 report the results for genders. The fall in ICT price is associated with increases in WFH for both males and females. The value of the estimated coefficient on the interaction term is not statistically significantly different across genders. The fall in ICT price is also associated with increases in WFH in high- and low-wage occupations. In this case, the value of the estimated coefficient on the interaction term is almost the same and statistically indistinguishable in occupation groups, even though WFH is more prevalent in high-wage occupations than in low-wage occupations. The results for occupation groups are reported in panels $F$ and $G$ of Table 5.[11]

# 5 Robustness Checks

To rule out other explanations for our main results, we conduct a range of robustness checks. We further report exclusively the results for the general WFH measure. We have checked, however, that all our results are qualitatively the same for WFH measures within different groups.

We first estimate specification (1) using two alternative measures for ICT dependence in industries to alleviate endogeneity and measurement concerns. Panel $A$ of Table 7 reports the results when we use the value of the share of ICT capital in total capital in US industries in 2008 as the dependence measure, instead of the average of the sample period. The estimated coefficient is very similar to our baseline estimate in Panel $A$ of Table 4. Next, we use as a measure of dependence the value of the share of ICT capital in total capital in industries of sample European countries averaged over the sample period. This dependence measure is more appropriate if there are significant structural differences in the production technology across countries. It can, however, attenuate the estimate of parameter $\beta$ if its variation across countries is because of temporary shocks. Panel $B$ of Table 7 reports the results. The estimated coefficient is somewhat lower than the baseline estimate suggesting that measurement error stemming from temporary shocks in this dependence measure can be attenuating the estimate.

It could be that the relationship we identify is the result of general structural changes, such as the substitution of capital for labor rather than changes in ICT prices. The substitution of capital for labor could increase the employment of those more willing to accept non-wage benefits such as WFH. To test this hypothesis, we compute the share of total non-ICT capital out of value added in US industries, average it over the sample

[11] We have also checked that our results hold in groups of workers with different levels of education, marital status, contract types (temporary/permanent), lengths of tenure, and cohabiting with and without children. We report these results in the Online Appendix.

period, interact it with the price of capital normalized by the price of the value added, and add this interaction to the specification (1). Panel $C$ of Table 7 reports the results. The coefficient estimate of the main interaction term almost does not change. In turn, the coefficient estimate of the newly added term is virtually insignificant. This result suggests that general structural changes, such as the substitution of capital for labor, are not likely to play a significant role in changes in WFH.

The changes in WFH in sample countries might be, at least to some degree, attributed to differences and changes in country-level regulations of labor markets. To study the role of regulations, we obtain a measure of overall labor market regulation from the Fraser Institute, which uses data from the Employing Workers project of the World Bank. The measure for overall labor market regulation attains higher values if regulations have more favorable provisions for flexible labor markets. The variation in these measures is at the country-year level, so it is controlled for by the country-year fixed effects in the specification (1). We interact it with ICT Dependence and add the interaction to the specification (1). Panel $D$ of Table 7 reports the results. The estimate of the coefficient on the main interaction term is virtually unaffected. In turn, the coefficient estimate on the interaction term for the labor market regulations is not statistically significant.[12]

The changes in ICT prices might be endogenous and affected by the demand for these technologies. It can pose challenges to the interpretation of the results if the demand for ICT in some of the industries has a particularly large effect on ICT prices. To alleviate such endogeneity concerns, we drop the industries likely to affect the aggregate demand for these technologies the most. More specifically, we exclude from the sample the industries where ICT capital is higher than the 75 percentile of the distribution of ICT capital across industries in each sample country and year. We estimate the specification (1) on this restricted sample and report the results in Panel $E$ of Table 7. The coefficient estimate on the interaction term is slightly smaller than the baseline estimate in Panel $A$ of Table 4. However, it is not statistically significantly different from the baseline

[12] Admittedly, we cannot identify overall country-level changes in WFH because of changes in the labor market regulations in the specification (1). Moreover, the synthetic indices of labor market regulations can mask various simultaneous changes in the labor markets that might not necessarily be related to WFH. This can warrant further study of the effects of labor market policies on WFH.

estimate.

Industries $J$ and $K$ have particularly high levels of ICT dependence. Even if this is not a concern given our identification strategy, we test the robustness of our results to their exclusion in Panel $F$. The estimate of the coefficient on the interaction term declines in magnitude but stays positive and statistically significant. Finally, we trim the data for WFH from below the 2nd percentile and above the 98th percentile within each country to exclude potential outliers. Panel $G$ offers the results with trimmed data. These results are almost identical to the baseline results.[13]

# 6 Conclusions

We use representative data from 12 European countries and industries and show considerable heterogeneity in the level of working from home (WFH) across industries and countries as well as age, gender, and occupation groups. We further show that WFH has steadily increased between 2008 and 2017 almost everywhere. It has also increased within age, gender, and occupation groups.

We explore these stylized trends following the arguments of, for example, Autor (2001) and Oettinger (2011) that the rise in WFH can be attributed to the rise in the use of information and communication technologies (ICT). We find that the share of employed individuals who report that they at least sometimes work from home has increased more in industries that depend more on ICT than in industries that depend less. Moreover, this differential change is larger in countries with a higher fall in ICT prices than in countries with a lower fall in ICT prices. This later result also holds in age, gender, and occupation groups. While we find no significant differences among gender and occupation groups, we find some notable differences among age groups. The positive association between the fall in ICT prices and WFH increases with age. An explanation for this result is that the preference for WFH increases with age because of home ownership and distaste for commuting, and opportunities to learn from on-site work decline with it.

All in all, our findings support the hypothesis that ICT facilitates and increases WFH.

[13] The Online Appendix reports additional robustness checks.

In particular, the advances in high-speed internet, cloud computing, video conferencing tools, and collaboration software that occurred during the period of study allowed an increase in WFH. The COVID-19 pandemic has propelled the use of ICT to facilitate WFH beyond the reported trend driven by the reduction of ICT prices. This may have increased the ICT dependence in some industries, implying a potential permanent increase in the share of employees WFH.

Our results are relevant for the debate on the “digital divide” since many of the employees who stand to benefit from the increase in the ability to work from home are most likely to have better digital skills. Falck et al. (2020) show that these skills are strongly related to higher labor market returns and increase with access to ICT infrastructure. Based on this, they suggest that increasing access to ICT infrastructure can help employees keep up with the current technological advances that change the demand for jobs (e.g., Acemoglu and Restrepo, 2018, Autor et al., 2003). It can be especially important to ensure access to ICT for those who live in remote areas or are socially disadvantaged (Zuo, 2021). In this regard, it can be important for governments to promote appropriate life-long-learning opportunities and motivate participation in ICT skill training for better social and labor market inclusion. Our results support these policy recommendations and suggest that the efforts to increase ICT skills and access to ICT might not be limited to higher pecuniary returns in the labor market. They can also be associated with increased opportunities of working (remotely) from home. As a result, policies motivating ICT skill acquisition and increasing access to ICT can reduce work commuting time and increase access to more remote labor markets. They can also be associated with a higher firm- and country-level resilience to local and global outbreaks, such as COVID-19.

# 7 Tables and Figures

Table 1: Working from Home and ICT in Sample Industries

| | | *A. Working from Home* | | | | | | *B. ICT* | |
|---|---|---|---|---|---|---|---|---|---|
| Industry Name | Industry Code | Obs. | Mean | SD | Min | Max | Δ | ICT Dependence | Share of ICT Capital |
| Agriculture, Forestry and Fishing | A | 120 | 0.103 | 0.082 | 0.000 | 0.317 | 0.001 | 0.002 | 0.005 |
| Mining and Quarrying | B | 120 | 0.075 | 0.074 | 0.000 | 0.311 | 0.055 | 0.006 | 0.014 |
| Manufacturing | C | 120 | 0.086 | 0.069 | 0.009 | 0.243 | 0.032 | 0.035 | 0.041 |
| Electricity, Gas, and Water Supply | D-E | 120 | 0.112 | 0.095 | 0.005 | 0.339 | 0.053 | 0.008 | 0.019 |
| Construction | F | 120 | 0.070 | 0.053 | 0.002 | 0.201 | 0.027 | 0.033 | 0.028 |
| Wholesale and Retail Trade; Repair of Vehicles | G | 120 | 0.085 | 0.060 | 0.007 | 0.238 | 0.031 | 0.070 | 0.059 |
| Transport and Storage | H | 120 | 0.059 | 0.043 | 0.003 | 0.180 | 0.014 | 0.031 | 0.022 |
| Accommodation and Food Services | I | 120 | 0.036 | 0.025 | 0.001 | 0.097 | 0.008 | 0.012 | 0.025 |
| Information and Communication | J | 120 | 0.306 | 0.178 | 0.032 | 0.627 | 0.113 | 0.244 | 0.272 |
| Financial and Insurance Activities | K | 120 | 0.172 | 0.114 | 0.011 | 0.426 | 0.081 | 0.128 | 0.170 |
| Real Estate Activities | L | 120 | 0.167 | 0.106 | 0.000 | 0.427 | 0.019 | 0.001 | 0.001 |
| Professional and Support Service Activities | M-N | 120 | 0.166 | 0.111 | 0.008 | 0.413 | 0.051 | 0.172 | 0.086 |

Note: Panel *A* of this table offers the descriptive statistics of WFH in sample industries. The number of observations corresponds to the number of sample countries and years. Δ refers to the change in the WFH over the sample period in each industry averaged across countries. Panel *B* offers the values of the measure of dependence on information technologies (ICT Dependence) and the country-year average value of the share of ICT capital in total capital in sample industries. See Table 8 in the Data Appendix for complete descriptions and sources of variables. Source: Own computations from EU-LFS and EU-KLEMS.

Table 2: Sample Countries, Working from Home, Correlations with ICT Dependence, and 1/ICT Price

| | | *A. Working from Home* | | | | | | *B. Correlations* | *C. Basic Statistics for 1/ICT Price* | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Country | Sample Period | 2008 | 2011 | 2014 | 2017 | Δ in HD Industries | Δ in LD Industries | ICT Dependence | Mean | SD | Min | Max | Δ |
| Austria | 2008-2017 | 0.148 | 0.164 | 0.163 | 0.162 | 0.028 | 0.001 | 0.865 | 1.114 | 0.098 | 0.991 | 1.262 | 0.271 |
| Czechia | 2008-2017 | 0.024 | 0.030 | 0.033 | 0.052 | 0.036 | 0.021 | 0.840 | 1.017 | 0.029 | 0.977 | 1.064 | 0.087 |
| Denmark | 2008-2017 | 0.202 | 0.227 | 0.238 | 0.266 | 0.061 | 0.066 | 0.791 | 1.076 | 0.096 | 0.951 | 1.250 | 0.299 |
| Finland | 2008-2017 | 0.150 | 0.162 | 0.196 | 0.248 | 0.149 | 0.047 | 0.620 | 1.150 | 0.173 | 0.847 | 1.383 | 0.536 |
| France | 2008-2017 | 0.104 | 0.132 | 0.112 | 0.135 | 0.043 | 0.019 | 0.947 | 1.245 | 0.256 | 0.878 | 1.561 | 0.683 |
| Germany | 2008-2017 | 0.088 | 0.061 | 0.071 | 0.076 | -0.009 | -0.016 | 0.928 | 1.051 | 0.055 | 0.961 | 1.125 | 0.164 |
| Italy | 2008-2017 | 0.013 | 0.013 | 0.014 | 0.019 | 0.007 | 0.006 | 0.881 | 0.973 | 0.025 | 0.944 | 1.017 | -0.053 |
| Slovakia | 2008-2017 | 0.046 | 0.064 | 0.074 | 0.068 | 0.031 | 0.013 | 0.837 | 0.992 | 0.034 | 0.922 | 1.023 | -0.084 |
| Slovenia | 2008-2017 | 0.084 | 0.123 | 0.145 | 0.137 | 0.094 | 0.012 | 0.864 | 1.095 | 0.091 | 0.962 | 1.205 | 0.242 |
| Spain | 2008-2016 | 0.012 | 0.021 | 0.017 | 0.023* | 0.013 | 0.001 | 0.954 | 1.037 | 0.062 | 0.930 | 1.124 | 0.194 |
| Sweden | 2008-2016 | 0.123 | 0.201 | 0.248 | 0.274* | 0.182 | 0.105 | 0.769 | 1.264 | 0.244 | 0.924 | 1.553 | 0.461 |
| UK | 2008-2017 | 0.178 | 0.191 | 0.206 | 0.196 | 0.028 | 0.008 | 0.873 | 1.008 | 0.087 | 0.861 | 1.128 | -0.267 |

Note: Columns 1 and 2 of this table list sample countries and period. Panel *A* offers the values of WFH averaged across industries in 2008, 2011, 2014, and 2017. It also offers the changes in WFH during the sample period in industries that have above the median value of ICT Dependence (HD Industries) and in industries that have below the median value of ICT Dependence (LD Industries). There is a "⋆" for Spain and Sweden for 2017 because we do not have ICT prices for these countries for that year. The changes in WFH in high and low dependence industries in the last two columns of Panel *A* are computed for 2008-2016 period for Spain and Sweden. Panel *B* offers the pairwise correlations of the measure of dependence on information technologies (ICT Dependence) and the shares of ICT capital in the industries of the sample European countries. All correlations are significant at least at the 5% level. Panel *C* offers basic statistics for the inverse of the price of information technologies (1/ICT Price). Column 5 of Panel *C* offers the change in 1/ICT Price over the sample period (Δ). See Table 8 in the Data Appendix for complete descriptions and sources of variables. Source: Own computations from EU-LFS and EU-KLEMS.

Table 3: Working from Home within Gender, Age, and Occupation Groups

| *A. Age Groups* | Obs | Mean | SD | Min | Max | Δ |
|---|---|---|---|---|---|---|
| Young | 1416 | 0.072 | 0.05 | 0.014 | 0.255 | 0.026 |
| Medium-Age | 1416 | 0.142 | 0.080 | 0.044 | 0.392 | 0.037 |
| Old | 1416 | 0.127 | 0.074 | 0.042 | 0.372 | 0.029 |
| *B. Gender* | Obs | Mean | SD | Min | Max | Δ |
| Male | 1416 | 0.193 | 0.106 | 0.062 | 0.433 | 0.028 |
| Female | 1416 | 0.165 | 0.080 | 0.053 | 0.347 | 0.046 |
| *C. Occupation Groups* | Obs | Mean | SD | Min | Max | Δ |
| High | 1416 | 0.219 | 0.052 | 0.109 | 0.392 | 0.036 |
| Low | 1416 | 0.049 | 0.031 | 0.014 | 0.15 | 0.018 |

Note: This table offers basic statistics for WFH in age, gender, and occupation groups. Δ refers to the change in the WFH over the sample period averaged across countries. The number of observations is (10 countries) × (12 industries) × (10 years) + (Spain and Sweden)× (12 industries) × (9 years). See Table 8 in the Data Appendix for complete descriptions and sources of variables.

Table 4: Main Results

| | *A. Baseline* |
|---|---|
| ICT Dependence × 1/ICT Price | 0.770*** |
| | (0.086) |
| Obs | 1416 |
| R2 (Partial) | 0.118 |

| *B. The Magnitude of the Predicted Effect* | |
|---|---|
| $\hat{\beta} \times \Delta 1/ICTPrice \times \Delta ICTDependence$ | 0.017 |
| $(WFH_{HD,2017} - WFH_{HD,2008}) - (WFH_{LD,2017} - WFH_{LD,2008})$ | 0.032 |
| Predicted Effect, % of actual | 53.939 |

Note: Panel *A* of this table offers the baseline (main) result from the estimation of the specification (1). Panel *B* offers the magnitude of the predicted effect of the fall in ICT prices on WFH in industries with a high ICT dependence relative to industries with a low ICT dependence. It also offers the actual differential change in WFH across low and high ICT dependence industries during the sample period, $(WFH_{HD,2017} - WFH_{HD,2008}) - (WFH_{LD,2017} - WFH_{LD,2008})$, and the percentage of the explained variation by the fall in ICT prices. Δ1/ICT Price is the average of Δ in Table 2. ΔICT Dependence is the difference between the averaged values of ICT Dependence in industries where ICT Dependence is higher than its sample median (HD) and in industries where ICT Dependence is lower than its sample median (LD). See Table 1 for the information on ICT Dependence and WFH across industries. The average changes in WFH in sample years in high and low dependence industries can be computed using data from Panel *A* of Table 2. See Table 8 in the Data Appendix for complete descriptions and sources of variables. The regression in Panel *A* includes country-industry and country-year dummies and uses the least-squares estimation method. Standard errors are in parentheses. Standard errors are bootstrapped and two-way clustered at industry- and country-year-level. The number of observations is (10 countries) × (12 industries) × (10 years) + (Spain and Sweden)× (12 industries) × (9 years). R2 (Partial) is the R-squared of the model where country-industry and country-year dummies have been partialled out. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 5: Results for Age, Gender, and Occupation Groups

| | Age Groups | | |
|---|---|---|---|
| | *A. Young* | *B. Medium-Age* | *C. Old* |
| ICT Dependence × 1/ICT Price | 0.418*** | 0.633*** | 1.001*** |
| | (0.134) | (0.110) | (0.122) |
| Obs | 1416 | 1416 | 1416 |
| R2 (Partial) | 0.011 | 0.037 | 0.086 |

| | Gender | | Occupation Groups | |
|---|---|---|---|---|
| | *D. Male* | *E. Female* | *F. High Wage* | *G. Low Wage* |
| ICT Dependence × 1/ICT Price | 0.790*** | 0.584*** | 0.561*** | 0.680*** |
| | (0.098) | (0.143) | (0.131) | (0.112) |
| Obs | 1416 | 1416 | 1416 | 1416 |
| R2 (Partial) | 0.070 | 0.018 | 0.018 | 0.111 |

Note: This table offers the results from the estimation of the specification (1) for age, gender, and occupation groups. See Table 8 in the Data Appendix for complete descriptions and sources of variables. All regressions include country-industry and country-year dummies and use the least-squares estimation method. Standard errors are in parentheses. Standard errors are bootstrapped and two-way clustered at industry- and country-year-level. R2 (Partial) is the R-squared of the model where country-industry and country-year dummies have been partialled out. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 6: Results for Age Groups by Marital Status

| | Age Groups (Single) | | |
|---|---|---|---|
| | *A. Young* | *B. Medium-Age* | *C. Old* |
| ICT Dependence | 0.412*** | 0.777*** | 0.963*** |
| × 1/ICT Price | (0.148) | (0.138) | (0.173) |
| Obs | 1416 | 1416 | 1415 |
| R2 (Partial) | 0.010 | 0.024 | 0.033 |
| | **Age Groups (Married)** | | |
| | *E. Young* | *F. Medium-Age* | *G. Old* |
| ICT Dependence | 0.571* | 0.601*** | 1.004*** |
| × 1/ICT Price | (0.327) | (0.157) | (0.147) |
| Obs | 1363 | 1416 | 1416 |
| R2 (Partial) | 0.003 | 0.016 | 0.067 |

Note: This table offers the results from the estimation of the specification (1) for the WFH computed within age and marital status groups. See Table 8 in the Data Appendix for complete descriptions and sources of variables. All regressions include country-industry and country-year dummies and use the least-squares estimation method. Standard errors are in parentheses. Standard errors are bootstrapped and two-way clustered at industry- and country-year-level. R2 (Partial) is the R-squared of the model where country-industry and country-year dummies have been partialled out. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

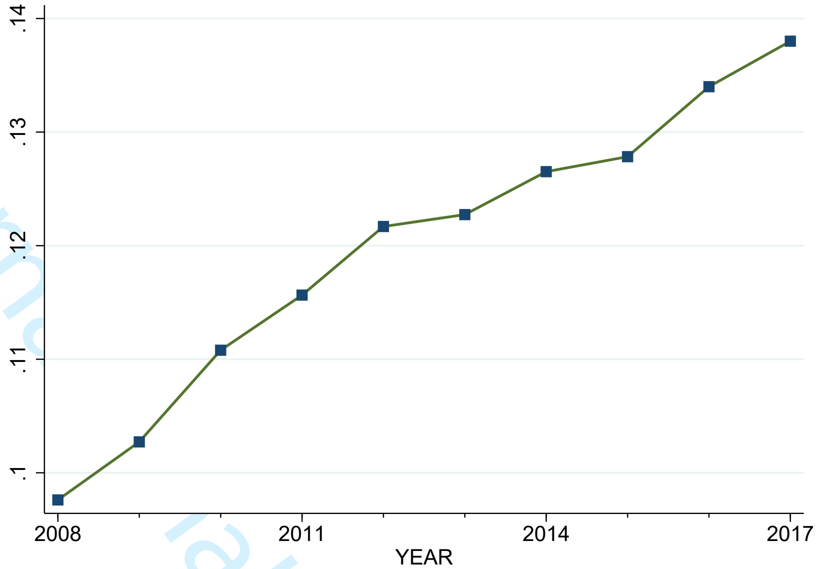
Table 7: Robustness Checks

| | A. *ICT Dependence (2008)* | B. *Share of ICT Capital* | C. *Capital Dependence* | D. *Regulations* |
|---|---|---|---|---|
| ICT Dependence<br>x 1/ICT Price | 0.752***<br>(0.092) | | 0.755***<br>(0.093) | 0.748***<br>(0.090) |
| Share of ICT Capital<br>x 1/ICT Price | | 0.588***<br>(0.068) | | |
| Non-ICT Capital Dependence<br>x 1/Capital Price | | | -0.778*<br>(0.446) | |
| ICT Dependence<br>x Labor Market Regulations | | | | 0.028<br>(0.023) |
| Obs | 1416 | 1416 | 1416 | 1416 |
| R2 (Partial) | 0.118 | 0.121 | 0.123 | 0.120 |

| | E. *W/o High ICT Using* | F. *W/o J and K* | G. *Trimmed* |
|---|---|---|---|
| ICT Dependence<br>x 1/ICT Price | 0.747***<br>(0.164) | 0.629***<br>(0.109) | 0.691***<br>(0.084) |
| Obs | 1180 | 1298 | 1374 |
| R2 (Partial) | 0.055 | 0.050 | 0.092 |

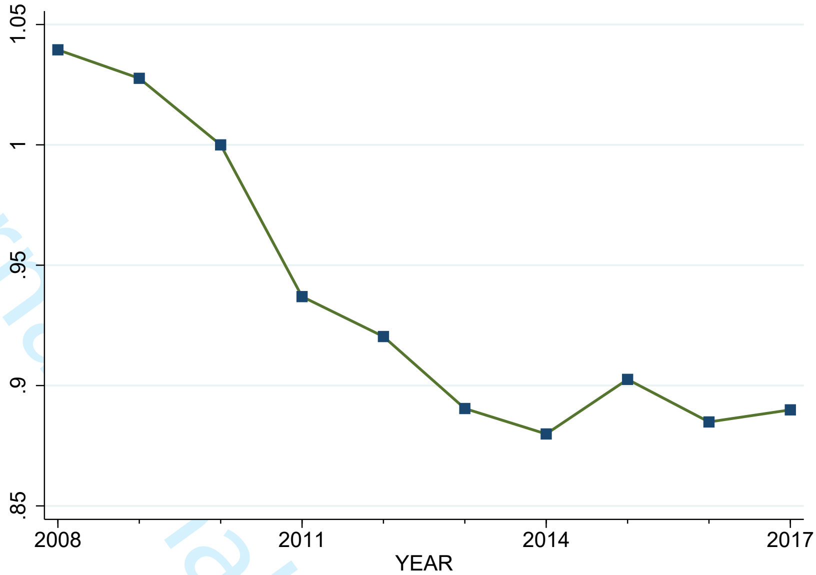
Note: This table offers the results from robustness check exercises. The dependant variable is WFH. Panels *A* and *B* offer the results from the estimation of the specification (1) using ICT Dependence (2008) and the Share of ICT Capital as the dependence measures. Panel *C* offers the results from the estimation of an augmented version of the specification (1) which has an additional interaction term. Panel *D* shows the results from the estimation of the specification (1) with additional interaction terms measuring regulations in the labor market. In Panel *E*, we exclude from the sample the industries where ICT capital is higher than the 75th percentile of the distribution of ICT capital across industries in each sample country and year. Industries *J* and *K* are excluded from the sample in Panel *F*. Finally, we trim the data for WFH within each country to exclude potential outliers. Panel *G* offers the results from the estimation of the specification (1) with trimmed data. These data exclude the values of WFH below the 2nd percentile and above the 98th percentile of the distribution of WFH (over industries and years) in each country. All regressions include country-industry and country-year dummies and use the least-squares estimation method. Standard errors are in parentheses. Standard errors are bootstrapped and two-way clustered at industry- and country-year-level. R2 (Partial) is the R-squared of the model where country-industry and country-year dummies have been partialled out. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Figure 1: Working from Home in Sample Countries




Note: This figure illustrates the trends in the WFH which is averaged across sample industries and countries. See 8 in the Data Appendix complete descriptions and sources of variables.

Figure 2: The Price of Information Technologies (ICT Price)




Note: This figure illustrates the evolution of the price of ICT relative to the price of capital (ICT Price). This relative price is averaged across countries. See Table 8 in the Data Appendix for complete descriptions and sources of variables.

# A Data Appendix

Table 8: Definitions and Sources of Variables

| Variable Name | Definition and Source |
|---|---|
| Capital Dependence | The ratio of non-ICT physical capital and value added in US industries averaged over the 2008-2017 period. Authors' calculations using data from EU KLEMS. |
| Capital Price | The price of investments in physical capital relative to the price of value added in sample countries. We use the inverse of this measure in estimations. Source: EU KLEMS. |
| ICT Dependence | The share of ICT capital in total capital in US industries averaged over the 2008-2017 period [as given by equation (6) in the Online Appendix]. ICT includes computing and communications equipment and computer software and databases. Authors' calculations using data from EU KLEMS. |
| ICT Dependence (2008) | The share of ICT capital in total capital in US industries in 2008 [as given by equation (6) in the Online Appendix]. Authors' calculations using data from EU KLEMS. |
| ICT Price | The price of investments in information technologies relative to the price of investments in physical capital in sample countries [$(p_{ICT})$ in the Online Appendix]. We use the inverse of this measure in estimations. Source: EU KLEMS. |
| Labor Market Regulations | The measure of labor market regulations. It includes hiring, firing and minimum wage regulations and regulations of centralized collective bargaining, hours of work, mandated cost of worker dismissal, and conscription. Higher values correspond to more regulations that favor more flexible labor markets. Source: Fraser Institute using Employing Workers project of the World Bank. |
| Share of ICT Capital | The share of ICT capital in total capital in sample industries and countries averaged over the sample period. Authors' calculations using data from EU KLEMS. |

**Table 8 – (Continued)**

| Variable Name | Definition and Source |
|---|---|
| WFH | The share of employed individuals who report that they work at home least sometimes out of the total number of employed individuals in each industry, country, and year. We use individual-level sample weights from the EU-LFS and exclude self-employed, family workers, and individuals older than 65 for computing this measure. See the Online Appendix for more details regarding this measure. Source: Authors' calculations using data from EU-LFS. |
| **Group** | **Description** |
| Age Group | There are three age groups: young (between 15 and 30), medium-age (between 30 and 45) and old (between 45 and 65). |
| Occupation Group | There are two occupation groups: high-wage occupations include the major groups 1, 2, and 3 from both classifications ISCO-88 and ISCO-08. Low-wage occupations include the rest of the major groups (from 4 to 9). |
| High ICT Using Industries | The industries where ICT capital is higher than the 75 percentile of the distribution of ICT capital across industries in each sample country and year. |
| Marital Status | There are two groups: married and single (single, divorced, and widowed are in one category). |

*Data Sources:* 2021 release of the EU Labour Force Survey database; 2019 release of the EU KLEMS database; Fraser Institute

*Country Sample:* Austria, Czechia, Denmark, Finland, France, Germany, Italy, Slovakia, Slovenia, Spain, Sweden, and the UK.

*Industry Sample (NACE rev. 2):* A, B, C, D-E, F, G, H, I, J, K, L and M-N.

*Sample Period:* 2008-2017 (2008-2016 for Spain and Sweden).

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# Online Appendix to "On Working from Home in European Countries"

# A Introduction

This document is an appendix to the paper "On Working from Home in European Countries". In this appendix, we offer a simple theoretical model that motivates the empirical methods used in the paper. We describe in detail the variable working from home (WFH) discussing the differences in data collection across countries. Finally, we provide further robustness checks and additional results that extend the main analysis provided in the paper.

# B Theoretical Background

We present a simple model to show how a fall in information and communication technologies (ICT) prices can increase WFH more in industries that depend more on ICT than in industries that depend less. We use this model to outline our assumptions and to motivate our empirical analysis.

Employees can work on-site and from home. The tasks that employees perform on-site, $n$, and from home, $h$, are imperfect substitutes in production. The elasticity of substitution between these tasks is given by $\varepsilon > 1$. The producers hire employees and combine ICT capital, $K_{ICT}$, with non-information technologies capital, $K_{NICT}$, to produce homogenous goods, $Y$. Their production function is given by

$$Y = \left[ \left( n^{\frac{\varepsilon-1}{\varepsilon}} + Ah^{\frac{\varepsilon-1}{\varepsilon}} \right)^{\frac{\varepsilon}{\varepsilon-1}} \right]^{\alpha} \left( K_{ICT}^{\sigma} K_{NICT}^{1-\sigma} \right)^{1-\alpha}, \tag{3}$$

where $A > 0$ is the productivity of tasks performed at home relative to the tasks performed at the workplace and $\alpha \in (0, 1)$ is a share parameter. The parameter $\sigma \in (0, 1)$ represents the elasticity of the composite capital input ($K = K_{ICT}^{\sigma} K_{NICT}^{1-\sigma}$) to $K_{ICT}$. In that sense, it shows the importance of $K_{ICT}$ in the composite capital input and the dependence of the industry production on $K_{ICT}$. Importantly, we also assume that $A$ is a monotonically increasing function of the ratio $K_{ICT}/K_{NICT}$.[1]

[1] To keep the model more tractable, we assume that the firm does not take this into account in its investment decisions.

We assume that workers are endowed with 1 unit of time that can be used for leisure, on-site work, and teleworking, and their utility from leisure is given by:

$$U = \ln\left(1 - L\left(\frac{1}{B_n}u_n + \frac{1}{B_h}u_h\right)\right), \tag{4}$$

where $L$ is the total labor supply, $Lu_n = n$, $Lu_h = h$, $u_n + u_h = 1$, and parameters $B_n > 0$ and $B_h > 0$ identify the relative preference of converting hours into on-site work and WFH. We normalize $B_n$ and set it to equal to 1.

We discuss learning during on-site work and increases in productivity and earnings stemming from this in the next section. In this regard, $B_h$ can be interpreted as the relative net benefit of converting hours into WFH which includes the preference of WFH and the potential of learning from on-site work.

The standard profit maximization in this model implies that

$$\frac{K_{ICT}}{K_{NICT}} = \frac{\sigma}{1-\sigma}\frac{p_{NICT}}{p_{ICT}}. \tag{5}$$

This result holds because of the Cobb-Douglas combination of $K_{ICT}$ and $K_{NICT}$ and suggests that the empirical moment for computing the dependence of the industry on ICT, $\sigma$, is given by:

$$\sigma = \frac{p_{ICT}K_{ICT}}{p_{ICT}K_{ICT} + p_{NICT}K_{NICT}}. \tag{6}$$

The labor supply decisions imply that the allocation of time to WFH $u_h$ is given by:

$$\frac{u_h}{1-u_h} = \left(B_h A\left(\frac{K_{ICT}}{K_{NICT}}\right)\right)^{\varepsilon}, \tag{7}$$

which is increasing with $K_{ICT}/K_{NICT}$.

We normalize $p_{NICT}$ and set it equal to 1. Using equation (5), it is straightforward to show that in this economy a fall in $p_{ICT}$ increases the ratio $K_{ICT}/K_{NICT}$:

$$\frac{\partial}{\partial p_{ICT}}\frac{K_{ICT}}{K_{NICT}} = -\frac{\sigma}{1-\sigma}\left(\frac{1}{p_{ICT}}\right)^2 < 0. \tag{8}$$

Moreover, the magnitude of this effect is larger in industries with a higher dependence on $K_{ICT}$. This is straightforward to verify by taking the derivative of the absolute value of (8) with respect to $\sigma$:

$$\frac{\partial}{\partial \sigma}\left|\frac{\partial}{\partial p_{ICT}}\frac{K_{ICT}}{K_{NICT}}\right| = \left(\frac{1}{1-\sigma}\frac{1}{p_{ICT}}\right)^2 > 0. \tag{9}$$

This, together with equation (7), implies that $u_h$ increases with the fall in $p_{ICT}$ and it increases more in industries that depend more on ICT than in industries that depend less. Moreover, these differential changes are larger in groups that have a higher $B_h$ according to equation (7).

These differential changes in $u_h$ should be observed in the data as differential changes in the share of WFH. We look exactly for such disparities and differential changes in the empirical specification (1).

## B.A Dynamic Model

We extend the model by incorporating learning while performing on-site work. To do so, we consider a model where individuals live for 3 periods. We assume that on-site work in earlier years enhances productivity in performing both on-site work and WFH later on. We also assume that the production function and the lifetime utility from leisure are now given by

$$Y_t = \left[\left(A_{e,n,t}n_t^{\frac{\varepsilon-1}{\varepsilon}} + A_{e,h,t}Ah_t^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}\right]^{\alpha}\left(K_{ICT}^{\sigma}K_{NICT}^{1-\sigma}\right)^{1-\alpha}, \tag{10}$$

$$U = \sum_{t=1}^{3}\gamma^{t-1}\ln\left(1 - L\times\left(\frac{1}{B_n}u_{n,t} + \frac{1}{B_{h,t}}u_{h,t}\right)\right), \tag{11}$$

where $A_{e,i,1} = 1$ and $A_{e,i,t} \geq 1$ for $i = n, h$ and $t = 2, 3$ represent the effects of learning during on-site work on the productivity of performing on-site work and WFH,

$$A_{e,i,2} = A_{e,i,2}\left(u_{n,1}L, A_{e,i,1}\right),$$
$$A_{e,i,3} = A_{e,i,3}\left(u_{n,2}L, A_{e,i,2}\right),$$

and $\gamma \in (0,1)$ is the discount rate. We assume that

$$\frac{\partial B_{h,t}}{\partial t} > 0, \frac{\partial A_{e,i,t}}{\partial u_{n,t-1}} > 0, \frac{\partial A_{e,i,t}}{\partial A_{e,i,t-1}} > 0, \frac{\partial^2 A_{e,i,t}}{\partial u_{n,t-1}\partial A_{e,i,t-1}} > 0, \frac{\partial A}{\partial K_{ICT}/K_{NICT}} > 0. \quad (12)$$

We consider first the case when the changes in $A_{e,i,t}$ are not internalized. In such a case, labor force allocations to on-site work and WFH by age are given by

$$\frac{u_{h,t}}{1-u_{h,t}} = \left(AB_{h,t}\frac{A_{e,h,t}}{A_{e,n,t}}\right)^{\varepsilon}, \quad (13)$$

where we have normalized the value of $B_n$ to 1 similarly to the main text. This expression is very similar to the expression in equation (5) in the paper where $B_h$ is replaced by $B_{h,t} \times A_{e,h,t}/A_{e,n,t}$. In this case, $u_{h,t}$ increases with age if the preference for and the productivity of WFH, $B_{h,t} \times A_{e,h,t}$, grow more than the productivity of working on-site $A_{e,n,t}$. Moreover, $u_{h,t}$ increases more in industries with a higher dependence on ICT than in industries with lower dependence with the fall of ICT prices, as $A$ is increasing in ICT dependence. Additionally, these differential changes are larger for older workers if $B_{h,t} \times A_{e,h,t}$ grows more by age than $A_{e,n,t}$.

In case when the changes in $A_{e,i,t}$ are internalized, labor force allocations to on-site work and WFH by age are given by

$$\frac{u_{h,t}}{1-u_{h,t}} = \left(AB_{h,t}\frac{A_{e,h,t}}{A_{e,n,t}}\Phi_t\right)^{\varepsilon}, \quad (14)$$

where

$$\begin{aligned}
\Phi_1 &= 1 - \gamma\frac{1-L\times l_1}{1-L\times l_2}\frac{1}{B_{h,2}}\frac{1}{A_{e,h,2}A}n_2\left[\left(\frac{u_{h,2}}{1-u_{h,2}}\right)^{\frac{1}{\varepsilon}}\frac{\partial A_{e,n,2}}{\partial n_1} + A\frac{u_{h,2}}{1-u_{h,2}}\frac{\partial A_{e,h,2}}{\partial n_1}\right] \\
&\quad -\gamma^2\frac{1-L\times l_1}{1-L\times l_3}\frac{1}{B_{h,3}}\frac{1}{A_{e,h,3}A}n_3\left[\left(\frac{u_{h,3}}{1-u_{h,3}}\right)^{\frac{1}{\varepsilon}}\frac{\partial A_{e,n,3}}{\partial n_1} + A\frac{u_{h,3}}{1-u_{h,3}}\frac{\partial A_{e,h,3}}{\partial n_1}\right], \\
\Phi_2 &= 1 - \gamma\frac{1-L\times l_2}{1-L\times l_3}\frac{1}{B_{h,3}}\frac{1}{A_{e,h,3}A}n_3\left[\left(\frac{u_{h,3}}{1-u_{h,3}}\right)^{\frac{1}{\varepsilon}}\frac{\partial A_{e,n,3}}{\partial n_2} + A\frac{u_{h,3}}{1-u_{h,3}}\frac{\partial A_{e,h,3}}{\partial n_2}\right], \\
\Phi_3 &= 1, \\
l_t &= \frac{1}{B_n}u_{n,t} + \frac{1}{B_{h,t}}u_{h,t}.
\end{aligned}$$

The expression in equation (14) is also very similar to the expression in the equation (5) in the main paper where $B_h$ is replaced by $B_{h,t} \times A_{e,h,t}/A_{e,n,t} \times \Phi_t$. It has to be the case that $\Phi_1$ and $\Phi_2$ are from $(0,1)$ since $u_{h,t} \in (0,1)$. There are negative terms in $\Phi_1$ and $\Phi_2$ because the young and medium-age workers allocate less time to teleworking when they take into the effect of working on-site on workplace learning and on their later productivity and earnings. Everything else equal, young workers have higher returns on learning from on-site work than medium-age workers, and medium-age workers have higher returns than old workers as long as $\Phi_1 < \Phi_2 < 1$.

This implies that WFH can increase with age because of two reasons. First, it can increase if the preference for and productivity of WFH increase more than the productivity of working on-site

$$\frac{\partial}{\partial t}\frac{B_{h,t}A_{e,h,t}}{A_{e,n,t}} > 0.$$

Second, it can also increase because younger workers have more opportunities to learn and improve their earnings while working on-site than older workers.

# C Working from Home Variable in the EU-LFS

Individuals are considered to work from home when there is an agreement with the employer and hours can be credited as working time in the EU-LFS. This excludes WFH for personal reasons, due to time constraints, and without compensation. Exceptions are Finland and Germany. In Finland, individuals are considered to work from home also in case when they do that voluntarily and if they finish leftover work from the day in the office at home. In contrast, in Germany, there are home-office provisions. For example, individuals should work on a computer provided by the employer if they use a computer for working at home.

Farmers are not considered to work from home when they work on their own farms. However, it is counted as work from home if farmers, for example, perform administrative work at home.[2]

The frequency of WFH is reported as "usually" if the respondents have worked from home for at least half of the working days of the last four weeks, "sometimes" if the respondents have worked at home for less than half of the working days of the last four weeks, and "never" if the respondents have not worked at home during the last four weeks. There is a slight variation in this rule in terms of the formulation of the question regarding working from, the coding of the responses, and the reference period in sample countries. The question about WFH in Austria asks about the frequency of WFH in the last three weeks. In France, it asks about WFH without a period of reference until 2013 and with a reference to the last four weeks from 2013 onward. The reference period in Germany is the last three months until 2016 and changes to the last four weeks afterward. Respondents are considered to work from home "usually" if they worked from home twice or more times per week in the last four weeks in Italy. They are considered to work from home "sometimes" if they worked from home less than twice a week. The respondents are considered to work from home "usually" in the UK if they report that they work on their main job mostly in their own home. They are considered to work from home "sometimes" if in their main job either they have spent at least one full day in the last week WFH, or they answer positively to the question if they ever do any paid or unpaid work at home.

This is an example of the question asked. It corresponds to Austria in the 2015 to 2020 questionnaires.

> The following questions deal with the period from Monday, .... to Sunday, .... (date of the reference period) (reference period: reference week + 3 weeks before). How often did you work from home during this time?
>
> Work at home is:
>
> - Teacher preparation times
> - Preparation time of people in field service occupations
> - Other work at home by agreement with the employer

[2] Similarly, it is not counted as WFH if the work is performed in a workplace that is adjacent to the house or the apartment and has its own entrance.

- Self-employed/farmers: professional activities only, pure Housework doesn't count!

Answers:

1. On at least half of the working days
2. Less often
3. Never

Our extended sample in the robustness checks includes the Netherlands. There are no records of responses to the question of whether the respondents "sometimes" work from home till 2015 for the Netherlands in the EU-LFS survey.

The stricter requirements regarding WFH might be the reason for the absence of a positive trend in WFH in Germany in our data. Nevertheless, there is a differential positive trend in Germany where WFH has declined less in industries that depend more on ICT as compared to industries that depend less.

The broad concordance among the questions about WFH across countries in the EU-LFS can alleviate some of the measurement concerns. For example, Mas and Pallais (2020) point out that it is often unclear in (other) surveys if WFH is considered to be a measure of work flexibility or an indicator of time pressure at the workplace and completion of tasks at home. Country-year fixed effects and our focus on industry-level variation are likely to further alleviate the effect of the existing differences on the estimate of $\beta$ in the specification (1). We have checked though that our main results remain virtually unaffected if we drop any one country from the sample. We have also checked that our results are robust to dropping country groups (1) Germany and Sweden; (2) Germany, Finland, and Sweden; (3) Germany, Finland, Sweden, and the UK; (4) Germany, Finland, France, Sweden, and the UK; (5) Germany, Finland, France, Italy, Sweden, and the UK; and (6) Austria, Germany, Finland, France, Italy, Sweden, and the UK.

# D Further Robustness Checks and Results

This section presents the results from further robustness check exercises. It also offers additional results. We conduct robustness checks with respect to the regression method, empirical specification, and sample. We present the results for the general WFH. We have performed all these robustness checks for all demographic, employment, and contract-type groups and have obtained results that are very similar to the results presented in the paper.

The WFH variable is from $(0, 1)$. We estimate the specification (1) using Tobit with $(0, 1)$ censoring and present the results in Panel $A$ of Table VIII. The estimate on the coefficient is almost the same as the baseline estimate reported in Panels $A$ of Table 4 of the paper. We also estimate the specification (1) using the Quantile regression method and present the results in Panel $B$ of Table VIII. The estimate on the coefficient is somewhat lower but not statistically different from the baseline estimate.

Our data also contain information from the Netherlands, Luxembourg, Baltic states Estonia, Lithuania, and Latvia, and NACE Rev. 2 industries O, P, Q, R, S, T, and U. We exclude these countries and industries from our main sample because of data imperfections and potential large state involvement in production. We estimate the main specification (1) using a sample that includes these countries and industries and report the results in Panel $C$ of Table VIII. The estimate on the coefficient is very close to the baseline estimate.

We also check that our results are robust to two alternative empirical specifications and their corresponding identifying variations. The first alternative empirical specification regresses the long difference in the WFH on the sample initial value of the share of ICT capital and country fixed effects and has the following form:

$$\Delta \text{WFH}_{i,c} = \beta_{LD,1} \times \text{Share of ICT Capital (2008)}_{i,c} + \sum_c \tilde{\xi}_c + \tilde{\eta}_{i,c}, \quad (15)$$

where $\Delta$ stands for the difference between 2017 and 2008 values (2016 and 2008 for Spain and Sweden), $\tilde{\xi}$ are country fixed effects and $\tilde{\eta}$ is an error term. We expect to obtain a positive estimate of $\beta_{LD,1}$ since it implies that as ICT prices fall industries that had a higher share of ICT Capital (2008) have higher growth in WFH over sample years as compared to industries that had a lower share of ICT Capital.

The second alternative empirical specification regresses the long difference in the WFH on the sample initial value of the share of ICT capital interacted with the long difference in 1/ICT Price and country fixed effects. It has the following form:

$$\begin{aligned}\Delta \text{WFH}_{i,c} &= \beta_{LD,2}\left[\text{Share of ICT Capital}_{i,c,2008} \times \Delta 1/\text{ICT Price}_{i,c}\right] \\ &\quad + \sum_{c} \hat{\xi}_c + \hat{\eta}_{i,c},\end{aligned} \tag{16}$$

where $\Delta$ stands for the difference between 2017 and 2008 values (2016 and 2008 for Spain and Sweden), $\hat{\xi}$ are country fixed effects, and $\hat{\eta}$ is an error term. This specification is closer to the specification (1) and especially when we use as a dependence variable the Share of ICT Capital. We expect that the coefficient on this interaction term to be larger than the coefficient on the Share of ICT Capital (2008) in specification (15) in case we are identifying the correct effect of the fall in ICT prices on WFH. This is because the estimated coefficient in the specification (15) can be expected to be attenuated since it is missing important information in such a case.

Panels $D$ and $E$ of Table VIII present the results from estimations of specifications (15) and (16). The estimates of $\beta_{LD,1}$ and $\beta_{LD,2}$ are positive and significant. Moreover, $\beta_{LD,2} > \beta_{LD,1}$ further suggests a correct identification of the effect of a fall in ICT prices on WFH.

## Education-Level, Marital Status, Contract Type, Tenure Length, and Children

We also retrieve from the EU-LFS database information about education levels, marital status, whether the contract is temporary or permanent (indefinite), the length of tenure in the same job, and cohabitation with children. There are three education levels in the EU-LFS: low, medium, and high. Low-level corresponds to pre-primary to lower-secondary education. Medium-level corresponds to secondary to post-secondary and non-tertiary education, and high-level corresponds to tertiary education. We use all three levels of education in our analysis. Marital status is either married or single which also includes divorced and widowed. We divide the length of tenure into two groups and consider less than 3 years as a short tenure and more than 3 years as a long tenure.

We estimate the specification (1) for these groups and report the results in Table IX. These results are broadly consistent with our baseline results reported in Panel $A$ of Table 4 of the main paper. The value of the estimated coefficient on the interaction term for highly educated employees is lower than the value of estimated coefficients for employees with medium- and low-level education. It is also statistically insignificant. However, these estimates are not statistically different. The value of the estimated coefficient for married workers is also statistically not different from the value of the estimated coefficient for single workers.

Panels $F$ to $I$ in Table IX present the estimated coefficients for different contract types and tenure lengths. The estimated coefficient is slightly smaller for temporary contracts and short-tenure groups than the estimated coefficient for permanent contracts and long-tenure groups. These results point toward the importance of learning during on-site work, which might be more relevant for employees with a temporary contract and a short tenure than employees with a permanent contract and a long tenure. However, the coefficients in these groups are not statistically significantly different.

Finally, panels $J$ and $K$ in Table IX report the results when we distinguish between employees cohabiting with children and employees not cohabiting with children. Having children at home might make WFH more difficult, as children can distract from work tasks. At the same time, WFH might be desirable to facilitate the family-work balance. According to our results, a fall in ICT prices increases WFH for employees cohabiting and not cohabiting with children. Although the coefficient for those who cohabit with children is somewhat larger, these coefficients are not statistically significantly different from each other.

## Additional and Unreported Robustness Checks

We have performed additional robustness checks. We do not report the results for brevity.

We use the share of employed individuals who report that they work at home at least sometimes out of the total number of employed individuals to measure WFH. The EU-LFS allows us to also compute the share of employed individuals who report that they usually work at home. We prefer the former measure to the latter for several reasons. The ICT do not necessarily need to lead to the performance of work almost entirely from home/remotely. Some of the work-related interactions and tasks might still be better and easier performed at the workplace. For example, firms such as Google/Alphabet plan to have a hybrid work week after the pandemic where most employees spend a few days in the office to focus on collaboration and the remainder in places where they work best. In turn, Adams-Prassl et al. (2022) run a survey asking individuals the share of their job tasks they can theoretically perform from home. Although a significant number of workers report values of 0 or 100%, most workers report values in between. The evidence and theoretical models also suggest that partial work from home can contribute to maintaining economic activity and mitigate the spread of epidemics/pandemics (Brotherhood and Jerbashian, 2023). Finally, those who usually work from home might have other reasons to do so than the availability of ICT.[3] Nevertheless, we have estimated the specification (1) using the share of employed individuals who report that they usually work from home as the dependent variable. The estimated coefficient is somewhat smaller than the baseline estimate in Table 4 of the main paper but positive and statistically significant.

We also check that our results are robust to various sample restrictions. WFH has fallen slightly in Germany and increased around twice in Sweden in the sample period. When we drop these countries the estimated coefficient on the interaction term is somewhat lower than the baseline estimate though it is not statistically significantly different. The relative price of ICT has declined relatively less in Czechia during the sample period. Moreover, it has somewhat increased in Italy, Slovakia, and the UK. This might be be-

[3] There are also significantly more observations in the EU-LFS when computing the share of employees who sometimes work from home than the share of employees who do so usually. This can alleviate concerns with measurement and variance arising from data sampling.

cause of larger increases in the demand for ICT and higher ICT price sensitivity in these countries. Dropping these countries from the sample does not significantly affect our results. Additionally, we have checked that our main results are robust to the exclusion of any one industry from the sample. Similarly, we have checked that our main results are robust to the exclusion of any one country.

We do not control for industry and year fixed effects in the baseline specification (1). We do so because most of the changes in ICT prices can be attributed to technological progress over time and these changes can be expected to have different effects on WFH in industries because of differences in ICT dependence across industries. As an additional robustness check, we have added industry-year fixed effects in the baseline specification (1). In this case, the identifying variation stems from the within country-industry-year variation in the interaction of ICT prices and ICT Dependence. The estimated coefficient is positive and statistically significant. It is close to the baseline estimate in Table 4 of the main paper but somewhat smaller.

The occupational classification changes from ISCO-88 to ISCO-08 in the EU-LFS in 2011. We have computed the share of employed individuals who report that they work at home least sometimes out of the total number of employed individuals in countries and years within 1-digit industries and 1-digit ISCO-08 occupations. We have estimated a specification similar to the baseline specification (1) within 1-digit ISCO-08 occupations using country-industry-occupation and country-year-occupation fixed effects and data from the 2011-2017 period. The estimated coefficient on the interaction term is smaller than the baseline estimate in Table 4 of the main paper but positive and statistically significant.

Changes in WFH might be also related to changes and improvements in management practices. These tend to be elusive though we try to capture them using data from the EU-LFS. We have computed the share of female managers, managers with a university degree, and managers younger than 45 in industries in sample countries. Managers are those who work in all 2-digit ISCO-88 occupations starting with 1 except 13, and in 2-digit ISCO-08 occupations starting with 1 except 14. We have estimated an augmented version of the specification where we include these shares. The estimated coefficient on the interaction term between ICT Dependence and ICT Price remains unaffected in all these regressions. The estimates of the coefficients on the shares of female managers and managers with a university degree are insignificant. In turn, the estimated coefficient is significant and positive for the share of managers younger than 45.

To further test the possible effects of regulations, we have obtained a measure of regulation of hours of work from the Fraser Institute. This measure attains higher values when working hours regulations are less restrictive. The variation in these measures is at country-year level which is absorbed by the country-year fixed effects in the specification (1). We interact this measure with ICT Dependence and add the interaction to the specification (1). The estimated coefficient is insignificant similar to the overall labor market regulation measure in $D$ of Table 7.

# Tables and Figures

Table I: Correlations among Working from Home within Age, Gender, Education-Level, Marital Status, and Occupation Groups

| *A. Age Groups* | Industry-Country-Year | Industry-Country | Industry | Country | Year |
|---|---|---|---|---|---|
| Young & Medium-Age | 0.810 | 0.928 | 0.970 | 0.974 | 0.925 |
| Young & Old | 0.774 | 0.908 | 0.975 | 0.954 | 0.888 |
| Medium-Age & Old | 0.916 | 0.971 | 0.992 | 0.982 | 0.969 |
| *B. Gender* | | | | | |
| Male & Female | 0.832 | 0.883 | 0.857 | 0.971 | 0.959 |
| *C. Occupation Groups* | | | | | |
| High & Low Wage | 0.674 | 0.738 | 0.900 | 0.913 | 0.905 |
| *D. Education-Levels* | | | | | |
| High & Medium | 0.553 | 0.728 | 0.769 | 0.953 | 0.666 |
| High & Low | 0.801 | 0.855 | 0.872 | 0.980 | 0.957 |
| Medium & Low | 0.721 | 0.910 | 0.949 | 0.974 | 0.721 |
| *E. Marital Status* | | | | | |
| Single & Married | 0.922 | 0.957 | 0.984 | 0.982 | 0.969 |
| *F. Contract Type* | | | | | |
| Temporary & Permanent | 0.749 | 0.894 | 0.982 | 0.937 | 0.893 |
| *G. Tenure Length* | | | | | |
| Short & Long | 0.921 | 0.971 | 0.987 | 0.994 | 0.966 |
| *H. Children* | | | | | |
| W & w/t Children | 0.912 | 0.981 | 0.992 | 0.996 | 0.935 |

Note: This table reports the pairwise correlations between working from home in age, gender, occupation, education level, marital status, contract type, and tenure length groups and workers who cohabit with children and workers who do not. In Column 2, we report correlations using data with a country-industry-year-level variation. In Column 3, we take averages across years and report correlations using data with a country-industry-level variation. In Column 4, we take averages across countries and years and report correlations using data with an industry-level variation. In Column 5, we take averages across industries and years and report correlations using data with a country-level variation. In Column 6, we take averages across countries and industries and report correlations using data with a yearly variation. All correlations are significant at least at the 5% level.

Table II: ANOVA for Working From Home

| Source | Partial SS | df | MS |
|---|---|---|---|
| Model | 18.773 | 1415 | 0.013 |
| | | | |
| Industry | 7.005 | 11 | 0.637 |
| Country | 7.753 | 11 | 0.705 |
| Industry × Country | 2.889 | 121 | 0.024 |
| Year | 0.199 | 9 | 0.022 |
| Year × Industry | 0.135 | 99 | 0.001 |
| Year × Country | 0.319 | 97 | 0.003 |
| Year × Industry × Country | 0.452 | 1067 | 0.000 |

Note: This table reports the results from an ANOVA exercise for the working from home variable. The variation in the data is at industry-country-year level, and we perform ANOVA along each of these dimensions.

Table III: Working from Home within Gender, Age, and Occupation Groups in Germany

| *A. Age Groups* | Obs | Mean | SD | Min | Max | Δ |
|---|---|---|---|---|---|---|
| Young | 120 | 0.047 | 0.044 | 0.000 | 0.261 | -0.027 |
| Medium-Age | 120 | 0.085 | 0.065 | 0.000 | 0.306 | -0.002 |
| Old | 120 | 0.076 | 0.057 | 0.000 | 0.254 | -0.011 |
| *B. Gender* | Obs | Mean | SD | Min | Max | Δ |
| Male | 120 | 0.155 | 0.113 | 0.000 | 0.405 | -0.040 |
| Female | 120 | 0.108 | 0.072 | 0.000 | 0.315 | -0.015 |
| *C. Occupation Groups* | Obs | Mean | SD | Min | Max | Δ |
| High | 120 | 0.138 | 0.064 | 0.000 | 0.319 | -0.024 |
| Low | 120 | 0.038 | 0.029 | 0.000 | 0.118 | -0.012 |

Note: This table offers basic statistics for working from home in age, gender, and occupation groups in Germany. Δ refers to the change in the WFH over the sample period. See Table 8 in the Data Appendix for complete descriptions and sources of variables.

Table IV: ANOVA for the Share of ICT Capital in US Industries

| Source | Partial SS | df | MS |
|---|---|---|---|
| Total | 0.626 | 109 | 0.006 |
| Industry | 0.621 | 11 | 0.056 |
| Year | 0.001 | 9 | 0.000 |
| Year × Industry | 0.002 | 89 | 0.000 |

Note: This table reports the results from an ANOVA exercise for the share of ICT capital in total capital in US Industries. We use the average of this share over the period 2008-2017 as the measure of ICT dependence. The variation in the data is at the industry-year level, and we perform ANOVA along each of these dimensions.

Table V: ANOVA for the Share of ICT Capital in Industries of Sample European Countries

| Source | Partial SS | df | MS |
|---|---|---|---|
| Total | 11.787 | 1415 | 0.008 |
| Industry | 8.497 | 11 | 0.772 |
| Country | 0.441 | 11 | 0.040 |
| Industry × Country | 2.650 | 121 | 0.022 |
| Year | 0.002 | 9 | 0.000 |
| Year × Industry | 0.014 | 99 | 0.000 |
| Year × Country | 0.012 | 97 | 0.000 |
| Year × Industry × Country | 0.138 | 1067 | 0.000 |

Note: This table reports the results from an ANOVA exercise for the share of ICT capital out of total capital in industries of sample European countries. The variation in the data is at the country-industry-year-level, and we perform ANOVA along each of these dimensions.

Table VI: ANOVA for ICT Price

| Source | Partial SS | df | MS |
|---|---|---|---|
| Total | 2.675 | 117 | 0.023 |
| Country | 0.970 | 11 | 0.088 |
| Year | 0.668 | 9 | 0.074 |
| Year × Country | 1.059 | 97 | 0.011 |

Note: This table reports the results from an ANOVA exercise for the price of information and communication technologies relative to the price of capital (ICT Price). The variation in the data is at country-year level, and we perform ANOVA along each of these dimensions.

Table VII: Working from Home within Demographic, Employment, and Contract Type Groups

| *A. Education-Level* | Obs | Mean | SD | Min | Max | Δ |
|---|---|---|---|---|---|---|
| High | 1416 | 0.212 | 0.067 | 0.078 | 0.403 | 0.035 |
| Medium | 1416 | 0.090 | 0.060 | 0.029 | 0.290 | 0.014 |
| Low | 1397 | 0.054 | 0.042 | 0.005 | 0.203 | 0.015 |
| *B. Marital Status* | Obs | Mean | SD | Min | Max | Δ |
| Single | 1416 | 0.147 | 0.087 | 0.048 | 0.371 | 0.032 |
| Married | 1416 | 0.206 | 0.101 | 0.07 | 0.452 | 0.038 |
| *C. Contract Type* | Obs | Mean | SD | Min | Max | Δ |
| Temporary | 1416 | 0.064 | 0.054 | 0.009 | 0.263 | 0.019 |
| Permanent/Indefinite | 1415 | 0.126 | 0.073 | 0.035 | 0.364 | 0.034 |
| *D. Tenure Length* | Obs | Mean | SD | Min | Max | Δ |
| Short | 1416 | 0.104 | 0.067 | 0.024 | 0.323 | 0.032 |
| Long | 1416 | 0.132 | 0.075 | 0.044 | 0.379 | 0.030 |
| *E. Children* | Obs | Mean | SD | Min | Max | Δ |
| With Children | 1068 | 0.102 | 0.063 | 0.031 | 0.333 | 0.025 |
| W/t Children | 1068 | 0.079 | 0.052 | 0.02 | 0.263 | 0.014 |

Note: This table offers basic statistics for working from home in education level, marital status, contract type, tenure length groups, and workers who cohabit with children and workers who do not. Δ refers to the change in the WFH over the sample period averaged over countries and industries. See Table 8 in the Data Appendix and Table X in the Further Robustness Checks and Results for complete descriptions and sources of variables.

Table VIII: Robustness Checks - Quantile and Tobit Regressions, All Sample, and Empirical Specification

| | A. Tobit | B. Quantile | C. All |
|---|---|---|---|
| ICT Dependence | 0.768*** | 0.554*** | 0.776*** |
| × 1/ICT Price | (0.077) | (0.080) | (0.084) |
| Obs | 1416 | 1416 | 2650 |
| R2 (Partial) | | | 0.024 |

| | D. Long Diff | E. Long Diff w/ Interaction |
|---|---|---|
| Share of ICT Capital (2008) | 0.288*** | |
| | (0.058) | |
| Share of ICT Capital (2008) | | 0.744*** |
| ×Δ 1/ICT Price | | (0.155) |
| Obs | 144 | 144 |
| R2 (Partial) | 0.621 | 0.611 |

Note: This table offers the results from additional robustness check exercises. See Table 8 in the Data Appendix and Table X in the Further Robustness Checks and Results for complete descriptions and sources of variables. The dependent variable is WFH in Panels $A - C$. Panels $A$ and $B$ report the results from the estimation of the specification (1) using Tobit$(0, 1)$ and Quantile regressions. Panel $C$ reports the results for a sample that includes Estonia, Latvia, Lithuania, and industries O, P, Q, R, S, T, and U. The dependent variable is the change of WFH over the period 2008-2016 in Panels $D - E$. Panel $D$ reports the results from the estimation of the specification (15). Panel $E$ reports the results from the estimation of the specification (16). Standard errors are in parentheses. Regressions in panels $A - C$ include country-industry and country-year dummies. Regressions in panels $D$ and $E$ include country dummies. Standard errors are bootstrapped and two-way clustered at industry- and country-year-level in panels $A-C$, and R2 (Partial) is the R-squared of the model where country-industry and country-year dummies have been partialled out. Standard errors are bootstrapped and clustered at country-level in panels $D-E$, and R2 (Partial) is the R-squared of the model where country dummies have been partialled out. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table IX: Results for Working from Home within Demographic, Employment, and Contract Type Groups

| | Education-Levels | | | Marital Status | |
|---|---|---|---|---|---|
| | *A. High* | *B. Medium* | *C. Low* | *D. Single* | *E. Married* |
| ICT Dependence × 1/ICT Price | 0.240 | 0.689*** | 0.685*** | 0.790*** | 0.825*** |
| | (0.157) | (0.132) | (0.161) | (0.095) | (0.118) |
| Obs | 1416 | 1416 | 1397 | 1416 | 1416 |
| R2 (Partial) | 0.003 | 0.071 | 0.016 | 0.063 | 0.068 |

| | Contract Type | | Length of Tenure | | Children | |
|---|---|---|---|---|---|---|
| | *F. Temporary* | *G. Permanent* | *H. Short* | *I. Long* | *J. With Children* | *K. W/t Children* |
| ICT Dependence × 1/ICT Price | 0.556*** | 0.777*** | 0.583*** | 0.890*** | 0.547*** | 0.411*** |
| | (0.159) | (0.103) | (0.123) | (0.105) | (0.122) | (0.127) |
| Obs | 1415 | 1416 | 1416 | 1416 | 1068 | 1068 |
| R2 (Partial) | 0.013 | 0.104 | 0.034 | 0.106 | 0.031 | 0.016 |

Note: This table offers the results from the estimation of the specification (1) for the WFH computed within education-level, marital status, contract type, tenure length groups, and workers who cohabit with children and workers who do not. See Table 8 in the Data Appendix and Table X in the Further Robustness Checks and Results for complete descriptions and sources of variables. All regressions include country-industry and country-year dummies and use the least-squares estimation method. Standard errors are in parentheses. Standard errors are bootstrapped and two-way clustered at industry- and country-year-level. R2 (Partial) is the R-squared of the model where country-industry and country-year dummies have been partialled out. *** indicates significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table X: Additional Definitions and Sources of Variables

| Variable Name | Definition and Source |
|---|---|
| Share of ICT Capital (2008) | The share of ICT capital in total capital in sample industries and countries in 2008. Authors' calculations using data from EU KLEMS. |
| Δ 1/ICT Price | The difference the value of 1/ICT Price in 2016 and its value in 2008. Source: EU KLEMS. |
| Δ WFH | The difference between the value of WFH in 2016 and its value in 2008. Source: Authors' calculations using data from EU-LFS. |
| **Group** | **Description** |
| Education-Level | There are three education-level groups: low, medium, and high. Low education level corresponds to pre-primary to lower-secondary education (0-2 of ISCED-97). Medium education level corresponds to secondary to post-secondary and non-tertiary education (3-4 of ISCED-97). High education level corresponds to tertiary education (5-6 of ISCED-97) |
| Children | Indicates if the respondent cohabits with or without children. This is a derived variable in the EU Labour Force Survey and has a lower number of observations. |
| Contract Type | There are two types of contracts: temporary and permanent/indefinite. |
| Tenure Length | There are two lengths of tenure on the same job: up to (including) 3 years and more than 3 years. |