The Impact of ICT on Working from Home: Evidence from EU Countries

Vahagn Jerbashian* Montserrat Vilalta-Bufí†

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Abstract

We use data from the EU Labour Force Survey for 14 countries and the 2008-2017 period and show that working from home has significantly increased in this period almost everywhere. We provide evidence that the fall in prices of information and communication technologies (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, we find that the positive association between the fall in ICT prices and working from home increases with age.

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

JEL classification: J23; J24; O33

*Universitat de Barcelona, CREB, BEAT, GLO, and CESifo. Email: vahagn.jerbashian@ub.edu.

†Universitat de Barcelona, CREB, and BEAT. Email: montsevilalta@ub.edu.

1 Introduction

Working from home has recently gained importance and prevalence because of the COVID-19 pandemic and lockdown policies (e.g., Brynjolfsson, Horton, Ozimek, Rock, Sharma, and TuYe, 2020, Eurofound, 2020). Many European countries are currently working towards easing regulations and promoting working from home.

We use data from the harmonized, individual-level EU Labour Force Survey (EU LFS) for 14 countries and the 2008-2017 period and establish that the share of employees who report that they at least sometimes work from home has been on a steady rise in almost all these countries (e.g., see Oettinger, 2011, Mateyka, Rapino, and Landivar, 2012, for evidence from the US). On average, it has increased from about 9 percent to 16 percent during the sample period. Working from home has also increased within age, gender, and occupation groups everywhere, except in Germany, where it has slightly declined during the sample period.

The steady rise in working from home can be attributed to the rise in the use of information and communication technologies (ICT) according to the arguments of many studies (e.g., Autor, 2001, Oettinger, 2011). These technologies include computers and the internet and can enable remote work. We empirically investigate this mechanism. We show that working from home has increased more in industries that depend more on ICT as compared to industries that depend less on ICT. In Germany, it has declined less in industries that have a higher dependence on ICT than in industries that have a lower dependence. We further utilize a difference-in-differences framework in the spirit of Rajan and Zingales (1998) and show that working from home 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. This result also holds within age, gender, and occupation groups. Taken together, these findings provide robust support for the hypothesis that information and communication technologies facilitate and increase working from home.

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). We find that the effect of the fall in ICT prices on the share of individuals working from home is not statistically different across gender and occupation groups. However, there are statistically significant and economically meaningful differences across age groups. Working from home has increased more among old than among medium-age with the fall in ICT prices. Moreover, working from home has increased more among medium-age than among young with the fall in ICT prices. All these results are robust to a wide range of specification checks and alternative identifying assumptions.

A possible explanation for the differences across age groups is that the preference for working from home increases with age and the opportunities for learning and productivity gains from working on-site decline with it. For example, young individuals usually reside in the house of their parents in Europe, whereas medium-age and old individuals live in their own house. This can hinder the willingness of young individuals to work from home as information and communication technologies proliferate. Younger workers may also have greater opportunities to learn from their colleagues and improve their productivity while working on-site than older workers. In turn, old individuals are usually averse to commute and travel which can amplify their willingness to work from home.[1]

A few earlier papers have studied alternative work arrangements and, in particular, working from home. Katz and Krueger (2019) show that the share of temporary, on-call and contract workers, and freelancers has increased in the 2005-2015 period in the United States. Edwards and Field-Hendrey (2002) emphasize the importance of working from home 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. According to Bloom, Kretschmer, and Van Reenen (2009), these results can hold because work from home can improve work-life balance.

[1] Allen, Johnson, Kiburz, and Shockley (2013) and Bal and Jansen (2016), among others, corroborate these arguments.

Working from home can also be associated with increased productivity according to Bloom, Liang, Roberts, and Ying (2015). Oettinger (2011) and Mateyka et al. (2012) document that working from home has steadily increased in the US during the past two decades. Oettinger (2011) also offers evidence showing that working from home has especially increased in occupations that use ICT more intensively.

The measurement and analysis of working from home has gained particular importance recently because of the COVID-19 pandemic.[2] Dingel and Neiman (2020) propose a task-based method, which relies on determining tasks that are incompatible with working from home, and evaluate the working from home capacity in the United States (similar approaches have been used for example by Boeri, Caiumi, and Paccagnella, 2020, Gottlieb, Grobovšek, Poschke, and Saltiel, 2021). There tend to be sizable differences in predictions regarding working from home capacity across studies utilizing such methods because of data limitations and differences in judgements regarding job characteristics that can be compatible with working from home. Nevertheless, the accumulated evidence suggests that such task-based methods can relatively accurately capture relevant variation in the working from home capacity when direct measures are not readily available (e.g., see Alipour, Falck, and Schüller, 2020, Gottlieb et al., 2021). In turn, several studies have used data from surveys and administrative employment statistics to measure the actual and potential working from home capacity (e.g., Adams-Prassl, Boneva, Golin, and Rauh, 2022, Alipour et al., 2020). These studies document significant differences of working from home across industries and occupations.

Our results complement the results of all these studies. We use data from the harmonized, individual-level EU Labour Force Survey and compute working from home using responses to questions regarding the incidence of working from home. We analyze changes in working from home and find that it has increased in industries of almost all sample countries and within age, gender, and occupation groups. We merge these data with data from the EU KLEMS database which allows us to investigate the association between

[2]The results of Brotherhood and Jerbashian (2020) and Fadinger and Schymik (2020) suggest that working from home can lead to lower losses in output and employment, and fewer infections and death casualties during pandemics such as the COVID-19.

working from home and information and communication technologies. In particular, we show that working from home has increased more in industries that depend more on ICT as compared to industries that depend less. We also find that the fall in ICT prices is associated with increased work from home. This uncovered association suggests that the capacity of working from home in countries depends on the availability and use of ICT in addition to the structure of employment. It also suggests that policy makers might target trade in ICT and the prices of these technologies, in addition to easing working from home regulations.[3]

These results also contribute to the literature that studies the economic impact of information and communication technologies (e.g., Czernich, Falck, Kretschmer, and Woessmann, 2011, Jerbashian and Kochanova, 2017, Jorgenson, Ho, and Stiroh, 2005) and, in particular, the effect of these technologies on labor demand and employment (e.g., Autor et al., 2003, Acemoglu and Autor, 2011, Jerbashian, 2019).[4]

The next section describes a simple model to motivate the empirical test. The third section describes the data and its sources and our identification strategy. The fourth section summarizes the results. The last section concludes.

2 Theoretical Background

We present a simple model to show that a fall in ICT prices would increase working from home more in industries that depend more on information and communication technologies than in industries that depend less. We also use this model to outline our assumptions and to set the stage for the 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 information and communication technologies capital, K_{ICT}, with non-information tech-

[3] The survey evidence suggests that businesses have invested in ICT to facilitate working from home during the COVID-19 pandemic (e.g., Barrero, Bloom, and Davis, 2021)

[4] Falck, Heimisch-Roecker, and Wiederhold (2020) show that there are significant wage returns to ICT skills. Our results suggest that there are also non-monetary returns to ICT skills such as better opportunities to work from home.

nologies capital, K_{NICT}, to produce homogenous goods, Y. Their production function is given by

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

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 σ represents the elasticity of the composite capital input ($K = K_{ICT}^{\sigma} K_{NICT}^{1-\sigma}$) to K_{ICT} and it takes values between 0 and 1. It shows the importance of K_{ICT} in the composite capital input and the dependence of the industry production on K_{ICT}. Importantly, we assume that A is a monotonically increasing function of the ratio K_{ICT}/K_{NICT}.

We assume that workers are endowed with 1 unit of time that can be used for leisure, on-site work, and teleworking. We assume that they have the following utility function:

$$U = \ln c + \ln \left(1 - L \left(\frac{1}{B_n} u_n + \frac{1}{B_h} u_h \right) \right), \tag{2}$$

where c is proportional to Y, L is 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 working from home. We normalize B_n and set it to equal to 1.

We abstract from learning during on-site work and increases in productivity and earnings stemming from this for simplicity. In this regard, B_h can be interpreted as the relative net benefit of converting hours into working from home that includes the preference of working from home and the potential of learning from on-site work.[5]

The standard profit maximization in this model implies that

$$\frac{K_{ICT}}{K_{NICT}} = \frac{\sigma}{1-\sigma} \frac{p_{NICT}}{p_{ICT}}. \tag{3}$$

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

[5]The Online Technical Appendix extends this model and adds inter-temporal choice and learning and productivity increases from on-site work.

information and communication technologies, σ, is given by:

$$\sigma = \frac{p_{ICT} K_{ICT}}{p_{ICT} K_{ICT} + p_{NICT} K_{NICT}}. \tag{4}$$

The labor supply decisions imply that the allocation of time to working from home u_h is given by:

$$\frac{u_h}{1 - u_h} = \left(B_h A \left(\frac{K_{ICT}}{K_{NICT}} \right) \right)^{\varepsilon}, \tag{5}$$

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

We normalize p_{NICT} and set it equal to 1. Using equation (3), it is straightforward to show that in this economy a fall in p_{ICT} increases the ratio K_{ICT}/K_{NICT}:

$$\frac{\partial}{\partial p_{ICT}} \frac{K_{ICT}}{K_{NICT}} = -\frac{\sigma}{1 - \sigma} \left(\frac{1}{p_{ICT}} \right)^2 < 0. \tag{6}$$

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 (6) with respect to σ:

$$\frac{\partial}{\partial \sigma} \left| \frac{\partial}{\partial p_{ICT}} \frac{K_{ICT}}{K_{NICT}} \right| = \left(\frac{1}{1 - \sigma} \frac{1}{p_{ICT}} \right)^2 > 0. \tag{7}$$

This, together with equation (5), 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 (5).

These differential changes in u_h should be observed in the data as differential changes in the share of working from home. We look exactly for such disparities and differential changes in the empirical specification.

3 Data and Empirical Methodology

The data for working from home are from the harmonized, individual-level EU Labour Force Survey (EU LFS). This survey asks employed individuals to report if they work from home usually, sometimes, or never. 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. We exclude from the sample self-employed, family workers, and the individuals who are older than 65. Industries have 1-digit NACE Rev. 2 coding. Our main sample excludes some of the industries because of potential large state involvement and a very limited number of observations in the labor force survey. Given data availability, the main sample includes 12 industries from 14 European countries and focuses on the period between 2008 and 2017.[6]

The first columns of Table 1 and Table 2 offer the list of sample industries and countries and column 2 of Table 2 offers the sample period for each country. Panels A in Table 1 and Table 2 and Figure 1 offer the average share of working from home and summarize its changes during the sample period. On average, working from home has increased by about 6.7 percentage points in the sample industries and countries.

Working from home and its change vary significantly across industries. Around 30% of workers in the Information and Communication Industry report working 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 working from home in the Accommodation and Food Service industry. On average, working from home has increased in all industries during the sample period according to the last column of Panel A in Table 1 and the levels of working from home are highly correlated with its changes. These changes are also large relative to the levels suggesting that changes in working from home are relatively recent phenomenon.

The levels of working from home and its changes also vary across countries according to

[6] There are data for earlier years than 2008 in the EU LFS database. We use data from 2008 onward because industry classification changes in the EE LFS database from NACE Rev. 1 to Rev. 2 in 2008, and the EU framework agreement about teleworking has gained a wider adoption after 2006.

Panel *A* of Table 2. Working from home has increased almost everywhere. It has increased less in the Southern European countries than in the Northern European countries. An exception is Germany, where working from home has declined from 8.8 percent to 7.6 percent during the sample period.

We also retrieve information from the EU LFS database on age, gender, and occupation. We do so to compute the share of employees working from home within each group. We create three age groups: young (younger than 30), medium-age (between 30 and 45), and old (between 45 and 65). In turn, we split the occupations into high and low wage groups motivated by arguments and evidence that information technologies complement high-wage occupations (e.g., Acemoglu and Autor, 2011, Jerbashian, 2019). The classification of occupations changes from ISCO-88 to ISCO-08 in 2011, and this way of splitting occupations has the additional 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.

Table 3 offers basic statistics for the working from home (WFH) variable within each of these categories. Young workers tend to work significantly less from home than medium-age and old workers according to Panel *A*. This can be because of the preference to work from home of older workers and learning opportunities during on-site work for younger workers, for example. There are no significant differences in terms of working from home between genders according to Panel *B*. The share of workers who report working from home at least sometimes is higher in high-wage occupations than in low-wage occupations according to Panel *C*. A rationale for this can be that the usual tasks of employees with high-wage occupations are easier to perform at home than the usual tasks of employees with low-wage occupations. Importantly, working from home has increased in all these categories during the sample period according to the last column of Table 3. The establishment of the trends in working from home as a stylized fact can be considered as one of the contributions of this paper.[7]

The data for information and communication technologies (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 information and communication technologies. This proxy needs to identify the technological differences across industries, i.e., σ in equation (4). We follow Rajan and Zingales (1998) and the literature motivated by their methodology and use data from US industries to accomplish this. The measure for industries' dependence on information and communication technologies (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.

The motivation for using data from US industries for ICT Dependence is that these industries are the world leaders in terms of investments in ICT and the level of ICT capital. Moreover, the 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 (e.g., Jerbashian and Kochanova, 2016, Nicoletti, von Rueden, and Andrews, 2020). 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

[7] Table I in the Online Appendix - Tables and Figures shows that 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. Table II reports the results from the analysis of variance of the working from home measure. Table III reports changes in working from home within groups in Germany.

countries. We also utilize the fact that there have been large investments in ICT over this period. The industry-level variation of the share of ICT capital in US industries accounts for nearly 100 percent of the total variation.[8] 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 according to 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.[9]

The value of ICT Dependence is highly correlated with the changes in working from home in sample industries according to Panel A of Table 2. This implies that the growth in working from home is stronger in industries that depend more on ICT. The last two columns of Panel A in Table 2 provide further evidence for this. We compute the average changes in working from home 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) in sample countries. Working from home has increased more industries with a high value of ICT Dependence as compared to 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 fallen less in industries with a high value of ICT Dependence as compared to industries with a low value of ICT Dependence.

We also need a measure for the price of information technologies p_{ICT}. To construct it, we obtain the price of investments in information and communication technologies in countries and years in our sample from the EU KLEMS database. This database contains data for the price of investments in ICT till 2017 for all sample countries except Spain and Sweden. The data for Spain and Sweden are till 2016. Following the model, we normalize the price of investments in ICT with the price of investments in non-ICT capital and use it as the measure for the price of information technologies (ICT Price).

[8] Table IV and Table V report these results in the Online Appendix - Tables and Figures.

[9] 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, Jerbashian and Kochanova, 2017). We perform a range of robustness checks for it in Table 7.

Table 2 offers basic statistics for ICT Price in Panel C. ICT Price displays significant variation over time and across countries (see also Table VI in the Online Appendix - Tables and Figures). 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.

Our empirical methodology follows the theoretical model, and our identification strategy is very similar to the one used by Rajan and Zingales (1998), Barone and Cingano (2011), and Jerbashian (2019). 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:

$$\begin{aligned}\mathrm{WFH}_{i,c,t} &= \beta\left[\text{Industry i's Dependence on }\mathrm{ICT}_i \times (1/\text{ICT Price})_{c,t}\right] \\ &\quad + \sum_c \sum_i \zeta_{c,i} + \sum_c \sum_t \xi_{c,t} + \eta_{i,c,t},\end{aligned} \tag{8}$$

where ζ and ξ are country-industry and country-year fixed effects respectively, and η is an error term.

The parameter of interest is β. It shows the effect of the fall in ICT prices on working from home. 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 working from home increases more with the fall in ICT prices in industries with higher ICT dependence as compared to industries with lower ICT dependence following the comparative statics result in (7). We perform the same estimation for each age, gender, and occupation group. We do not have *a priori* expectations about differences across these groups.

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

Before reporting the estimation results, it is worth outlining the interpretation of the coefficient β and presenting a non-parametric estimate of the effect of the fall in ICT prices on working from home. Roughly speaking, the difference-in-differences estimator in the specification (8) splits the sample into four groups according to the magnitude of the fall in ICT prices and the level of ICT dependence. These four groups are composed of the industry-country pairs with high fall in prices and high dependence (HF&HD), industry-country pairs with high fall in prices and low dependence (HF&LD), pairs with low fall in prices and high dependence (LF&HD), and pairs with low fall in prices and low dependence (LF&LD). An interpretation of β and a non-parametric estimate of the effect of the fall in ICT prices on working from home is given by the difference in the trends of working from home between HF&HD industry-country pairs relative to HF&LD industry-country pairs and LF&HD pairs relative to LF&LD pairs. This effect is positive if working from home grows at a higher rate in HF&HD industry-country pairs relative to HF&LD industry-country pairs than in LF&HD pairs relative to LF&LD pairs.

We take the residuals from a regression of the WFH on country-industry and country-year dummies to illustrate the existence of such differential trends. Figure 3 shows that there are such disparities and that working from home has increased more rapidly in industries with high ICT dependence relative to industries with low ICT dependence, with the fall in ICT prices.

4 Results

Panel A of Table 4 reports the baseline estimate of β from the specification (8) using our main sample. The coefficient is positive and significant. This implies that working from home increases with the fall in ICT prices and this increase is larger in industries that depend more on ICT as compared to industries that depend less on ICT.[10]

One way we can quantify these results and show their economic significance is as follows. We compute the average change in 1/ICT Price in sample period (Δ1/ICT Price). Further, we compute 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 (ΔICT Dependence). Finally, we compute

$$\hat{\beta} \times \Delta 1/\text{ICT Price} \times \Delta\text{ICT Dependence}. \tag{9}$$

Panel B of Table 4 reports the computed effect, and it is 0.019. We also compute the changes in working from home during the sample period in industries with higher than the median ICT Dependence and industries with lower than the median ICT Dependence. Finally, we compute the difference between these changes, and it is 0.034. This suggests that the fall in ICT prices has a strong effect on working from home and explains nearly 50 percent in the actual variation of the WFH variable corresponding to the empirical specification.[11]

We also estimate the specification (8) 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.

According to panels $A - C$ of Table 5, the effect of the fall in ICT prices on working from home increases with age. The differences in preferences for working from home and

[10]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 working from home. We provide a detailed discussion in the Online Appendix - Further Robustness Checks and Results.

[11]According to Table VI in the Online Appendix - Tables and Figures, the country-level variation in ICT prices is as important as yearly and country-year-level variation. This suggests that there is a room for policies that affect ICT prices and, subsequently, can have large effects on working from home.

learning opportunities from on-site work across age groups may explain these results. Young individuals usually reside in the house of their parents and have limited personal space in European countries in contrast to medium and old-age individuals who usually live in their own houses. In turn, old age individuals tend to be more averse to commuting than medium-age and young individuals. Younger workers may also have better opportunities to learn from working on-site than older workers.

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 a stronger preference for working from home. In such a case, we expect that married young individuals behave similarly to medium-age 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 effect of the fall in ICT prices on working from home strictly increases with age for single individuals. In contrast, the effect of the fall in ICT prices on working from home among married young individuals is larger and closer to the effect on working from home among medium-age and old individuals.

Panels D and E of Table 5 report the results for genders. The fall in ICT price is associated with increases in working from home for both males and females. The value of the estimated coefficient on the interaction term is larger for males than for females but these estimates are not statistically significantly different. There are almost no differences also between the effects of the fall in ICT prices on working from home in high- and low-wage occupations, even though working from home 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.[12]

In an attempt to rule out other explanations for our main results, we conduct a range

[12]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 - Further Robustness Checks and Results.

of robustness checks. We further report exclusively the results for the general working from home measure. We have checked, however, that all our results are qualitatively the same for working from home measures within different groups.

We first estimate specification (8) 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 sample initial value of the share of ICT capital in total capital in US industries as the dependence measure. 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 years. Such a measure of dependence is more appropriate if there are significant structural differences in the parameter σ across countries. It can, however, attenuate the estimate of parameter β 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 effect that we identify is not because of the fall in ICT prices but rather because of general structural changes in sample industries such as the substitution of capital for labor. This substitution could increase the employment of those who are more willing to accept non-wage benefits such as working from home. 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 period, interact it with the price of capital normalized by the price of the value added and add this interaction to the specification (8). Panel C of Table 7 reports the results. The estimate of the coefficient on the main interaction term almost does not change. In turn, the estimate of the coefficient on the newly added term is small. It is statistically significant, but very marginally. This suggests that general structural changes such as the substitution of capital for labor are not likely to play a significant role in changes in working from home.

Working from home has significantly increased in the Netherlands in 2015. It has declined in Germany during the sample period, and its trends in some industries in Luxembourg and Sweden seem to be considerably larger than the within country average. These changes and differences might be at least to some degree attributed to differences and changes in country-level regulations of labor markets and flexible work. For example, the Flexible Work Act (Wet flexibel werken) in the Netherlands has been in force since 2016. When this act covers various employment conditions, one of its provisions states that employees can request the employer to change the place of their work after working for the firm for 6 months. To study the role of regulations, we obtain measures of overall labor market regulation and regulation of hours of work from the Fraser institute which are based on 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. In turn, the measure for regulation of hours of work 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 (8). We interact these measures with ICT Dependence and add the interaction to the specification (8). Panel D of Table 7 reports the results. The estimate of the coefficient on the main interaction term somewhat declines but remains statistically indistinguishable from the baseline estimate. The estimates of the coefficients on the interaction terms for the labor market regulations are statistically significant. According to the last column of Panel D, working from home increases more in industries that depend more on ICT as compared to industries that depend less especially with regulations that favor more flexible hours of work. This evidence suggests that labor market regulations can also play a significant role for changes in working from home.[13]

We also check that our results are robust to various sample restrictions. We drop Germany, Luxembourg, Sweden and data for the Netherlands from 2015, 2016 and 2017 and report the results in Panel A of Table 8. The estimated coefficient on the interaction term is somewhat lower than the baseline estimate though it is not statistically signifi-

[13]Admittedly, such synthetic indices of labor market regulations can mask various simultaneous regulatory changes in the labor markets. This can warrant further studies of the effects of labor market policies on working from home.

cantly different. The relative price of information and communication technologies has declined relatively less in Czechia and Luxembourg during the sample period. Moreover, it has somewhat increased in Italy, Slovakia, and the UK. This might be because of larger increases in the demand for ICT and higher ICT price sensitivity in these countries. Panel B of Table 8 shows that dropping these countries from the sample does not significantly affect our results.

The changes in ICT prices might be endogenous and affected by the demand for these technologies. This can pose challenges for the identification if the demand for ICT in some of the industries has a particularly large effect on ICT prices. In an attempt to alleviate such endogeneity concerns, we drop the industries that are likely to affect the aggregate demand for these technologies the most. More specifically, we drop 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 (8) on this restricted sample and report the results in Panel C of Table 8. The estimate of the coefficient 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 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 D. The estimate of the coefficient on the interaction term declines in magnitude but stays positive and statistically significant. Finally, we trim the data for working from home from below the 2nd percentile and above the 98th percentile within each country to further exclude potential outliers. Panel E offers the results with trimmed data. These results are almost identical to the baseline results.[14]

5 Conclusions

We use data from European countries and industries and show that working from home has steadily increased during the period between 2008 and 2017 almost everywhere. The

[14] The Online Appendix - Further Robustness Checks and Results reports additional robustness checks.

rise in working from home can be attributed to the rise in the use of information and communication technologies (e.g., Autor, 2001). We empirically investigate this hypothesis and find that the share of employed individuals who report that they at least sometimes work from home has increased with the fall in ICT prices. This 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 working from home increases with age. An explanation for this result is that the preference for working from home 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 provide robust support for the hypothesis that information and communication technologies facilitate and increase working from home. This uncovered association suggests that ICT can affect the capacity of working from home in countries. Our findings also highlight the potential role of policies that target ICT prices and favor flexible work for promoting working from home.

6 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	140	0.114	0.098	0.000	0.449	0.025	0.002	0.004
Mining and Quarrying	B	130	0.080	0.081	0.000	0.344	0.073	0.006	0.014
Manufacturing	C	140	0.092	0.071	0.009	0.274	0.053	0.035	0.040
Electricity, Gas, and Water Supply	D-E	140	0.120	0.102	0.000	0.447	0.093	0.008	0.023
Construction	F	140	0.077	0.057	0.002	0.228	0.045	0.033	0.032
Wholesale and Retail Trade; Repair of Vehicles	G	140	0.087	0.061	0.007	0.238	0.046	0.070	0.065
Transport and Storage	H	140	0.064	0.048	0.003	0.234	0.032	0.031	0.022
Accommodation and Food Services	I	140	0.039	0.030	0.001	0.162	0.016	0.012	0.029
Information and Communication	J	140	0.304	0.175	0.032	0.633	0.153	0.244	0.261
Financial and Insurance Activities	K	140	0.178	0.125	0.011	0.624	0.121	0.128	0.168
Real Estate Activities	L	140	0.176	0.118	0.000	0.581	0.055	0.001	0.001
Professional and Support Service Activities	M-N	140	0.171	0.111	0.008	0.413	0.082	0.172	0.093

Note: Panel *A* of this table offers the descriptive statistics of working from home in sample industries. The number of observations corresponds to the number of sample countries and years. We drop industry B for Luxembourg because of the very limited number of observations. 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 9 in the Data Appendix for complete descriptions and sources of variables.

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
Luxembourg	2008-2017	0.066	0.145	0.209	0.280	0.233	0.192	0.888	1.037	0.033	0.990	1.093	0.078
Netherlands	2008-2017	0.061	0.071	0.080	0.299	0.266	0.212	0.903	1.043	0.080	0.877	1.140	0.263
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⋆	0.006	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 working from home averaged across industries in 2008, 2001, 2014, and 2017. It also offers the changes in working from home 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 $\star$ for Spain and Sweden for 2017 because we do not have ICT prices for these countries for that year. The changes in working from home 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 9 in the Data Appendix for complete descriptions and sources of variables.

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

A. Age Groups	Obs	Mean	SD	Min	Max	Δ
Young	1645	0.078	0.052	0.015	0.277	0.049
Medium-Age	1646	0.147	0.081	0.045	0.422	0.074
Old	1646	0.133	0.076	0.041	0.403	0.055
B. Gender	Obs	Mean	SD	Min	Max	Δ
Male	1646	0.200	0.109	0.060	0.458	0.061
Female	1646	0.168	0.084	0.049	0.375	0.078
C. Occupation Groups	Obs	Mean	SD	Min	Max	Δ
High	1646	0.223	0.057	0.108	0.427	0.080
Low	1646	0.055	0.033	0.015	0.157	0.037

Note: This table offers basic statistics for working from home 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 (11 countries) × (12 industries) × (10 years) + (Luxembourg) × (11 industries) × (10 years) + (Spain and Sweden)× (12 industries) × (9 years). See Table 9 in the Data Appendix for complete descriptions and sources of variables.

Table 4: Main Results

A. The Baseline Estimate of β	
ICT Dependence x 1/ICT Price	0.867*** (0.104)
Obs	1646
R2 (Partial)	0.068

B. The Magnitude of the Predicted Effect	
$\hat{\beta} \times \Delta 1/\text{ICT Price} \times \Delta\text{ICT Dependence}$	0.019
$(WFH_{HD,2017} - WFH_{HD,2008}) - (WFH_{LD,2017} - WFH_{LD,2008})$	0.034
Predicted Effect, % of actual	55.104

Note: Panel *A* of this table offers the baseline result from the estimation of the specification (8). Panel *B* offers the magnitude of the predicted effect of the fall in ICT prices on working from home in industries with a high ICT dependence relative to industries with a low ICT dependence. It also offers the actual differential change in working from home 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 working from home in sample years in high and low dependence industries can be computed using data from Panel *A* of Table 2. See Table 9 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 (11 countries) × (12 industries) × (10 years) + (Luxembourg) × (11 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 $\times$ 1/ICT Price	0.489*** (0.139)	0.744*** (0.116)	1.098*** (0.132)	
Obs	1645	1646	1646	
R2 (Partial)	0.009	0.026	0.054	
	Gender		Occupation Groups	
	D. Male	*E. Female*	*F. High Wage*	*G. Low Wage*
ICT Dependence $\times$ 1/ICT Price	0.902*** (0.103)	0.656*** (0.149)	0.635*** (0.126)	0.678*** (0.112)
Obs	1646	1646	1646	1646
R2 (Partial)	0.056	0.014	0.014	0.057

Note: This table offers the results from the estimation of the specification (8) for age, gender, and occupation groups. See Table 9 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	0.478***	0.854***	1.067***
× 1/ICT Price	(0.148)	(0.155)	(0.181)
Obs	1645	1645	1643
R2 (Partial)	0.007	0.014	0.021
	Age Groups (Married)		
	E. Young	*F. Medium-Age*	*G. Old*
ICT Dependence	0.583*	0.725***	1.090***
× 1/ICT Price	(0.312)	(0.165)	(0.153)
Obs	1577	1645	1645
R2 (Partial)	0.002	0.014	0.043

Note: This table offers the results from the estimation of the specification (8) for the WFH computed within age and marital status groups. See Table 9 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 - Measures and Additional Variables

	A. ICT Dependence (2008)	*B. Share of ICT Capital*	*C. Capital Dependence*
ICT Dependence	0.844***		0.881***
× 1/ICT Price	(0.094)		(0.092)
Share of ICT Capital		0.605***	
× 1/ICT Price		(0.075)	
Non-ICT Capital Dependence			-0.019*
× 1/Capital Price			(0.011)
Obs	1646	1646	1634
R2 (Partial)	0.068	0.057	0.074

	D. Labor Market Regulations		
	Overall	*Hours*	*Overall and Hours*
ICT Dependence	0.806***	0.789***	0.794***
× 1/ICT Price	(0.086)	(0.089)	(0.088)
ICT Dependence	0.065**		-0.008
× Labor Market Regulations	(0.031)		(0.036)
ICT Dependence		0.058***	0.060**
× Hours Regulations		(0.020)	(0.026)
Obs	1646	1646	1646
R2 (Partial)	0.073	0.086	0.086

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 (8) 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 (8) which has an additional interaction term. The number of observations is 1634 in Panels *C* since the non-ICT capital dependence measure has a lower number of observations. Panel *D* shows the results from the estimation of the specification (8) with additional interaction terms measuring regulations in the labor market. 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.

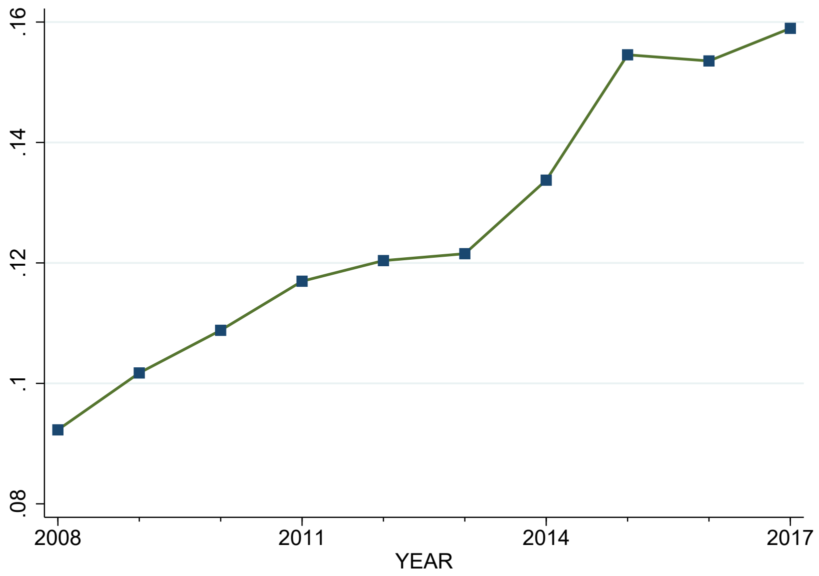
Table 8: Robustness Checks - Sample Restrictions

	A. W/o DE, LU, SE and NL (2015-2017)	B. W/o CZ, IT, LU *SK and UK*
ICT Dependence $\times$ 1/ICT Price	0.681***	0.920***
	(0.116)	(0.100)
Obs	1272	1056
R2 (Partial)	0.076	0.095

	C. W/o High ICT Using	*D. W/o J and K*	*E. Trimmed*
ICT Dependence $\times$ 1/ICT Price	0.841***	0.441***	0.776***
	(0.156)	(0.114)	(0.099)
Obs	1370	1370	1596
R2 (Partial)	0.030	0.010	0.056

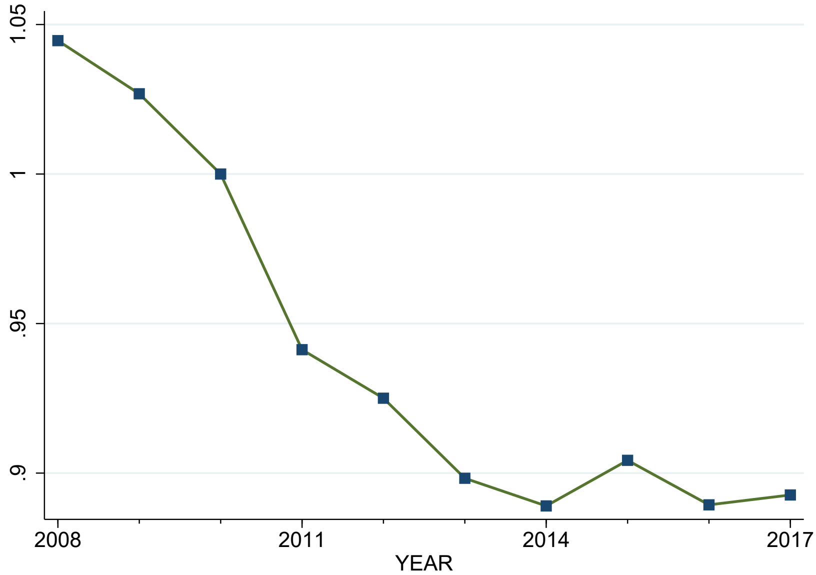
Note: This table offers the results from robustness check exercises. The dependant variable is WFH. We exclude from the sample Germany, Luxembourg, Sweden and drop data from the Netherlands for 2015, 2016 and 2017 in Panel *A*. We exclude from the sample Czechia, Italy, Luxembourg, Slovakia, and the UK in Panel *B*. In Panel *C*, 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 *D*. Finally, we trim the data for working from home within each country to exclude potential outliers. Panel *E* offers the results from the estimation of the specification (8) 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



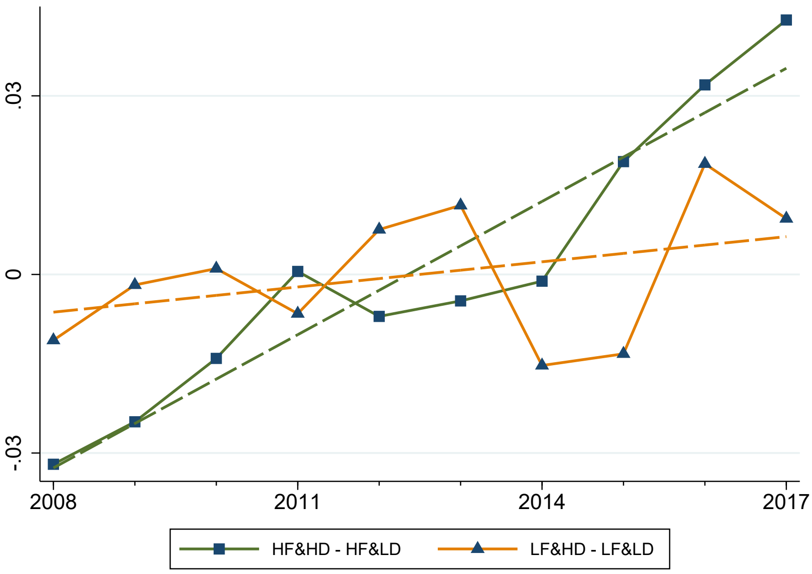
Note: This figure illustrates the trends in the WFH which is averaged across sample industries and countries. See 9 in the Data Appendix complete descriptions and sources of variables.

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



Note: This figure illustrates the evolution of the price of information and communication technologies relative to the price of capital (ICT Price). This relative price is averaged across countries. See Table 9 in the Data Appendix for complete descriptions and sources of variables.

Figure 3: Working from Home in High and Low ICT Dependence Industries



Note: This figure illustrates the differences in the trends in the working from home variable (WFH) in industry-country pairs with high and low ICT dependence and high and low fall in ICT prices. The curves with square tick symbols are the difference between WFH in industries with high ICT Dependence and industries with low ICT Dependence in countries where the fall in ICT Price is relatively high (HF&HD - HF&LD). The curves with triangle tick symbols are the difference between WFH in industries with high ICT Dependence and industries with low ICT Dependence in countries where the fall in ICT Price is relatively low (LF&HD - LF&LD). The curves in this figure are the residuals from an OLS regression of WFH on country-industry and country-year dummies. In each of the four groups, these shares are averaged over countries and industries. An industry has high (low) dependence on ICT if its ICT Dependence is above (below) the average ICT Dependence across industries. The fall in ICT Price in a country is relatively high (low) if the fall in ICT Price in that country is lower (higher) than the average change in ICT Price across countries. See Table 9 in the Data Appendix for complete descriptions and sources of variables.

A Data Appendix

Table 9: 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 (4). 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 (4). Authors' calculations using data from EU KLEMS.
Hours Regulations	The measure of regulations of hours of work. It considers regulations that, for example, impose restrictions on night, holiday, and overtime work and on the length of the work week. Higher values correspond to more flexible regulations of work hours. Source: Fraser Institute using Employing Workers project of the World Bank.
ICT Price	The price of investments in information and communication technologies relative to the price of investments in physical capital in sample countries (p_{ICT}). 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.

Table 9 – (Continued)

Variable Name	Definition and Source
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.
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. 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.

Country Sample: Austria, Czechia, Denmark, Finland, France, Germany, Italy, Luxembourg, the Netherlands, 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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B Online Technical Appendix

We extend the model presented in the main text 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 the productivity in performing both on-site work and working from home later on. We also assume that the production function and the life-time utility function are now given by

$$\begin{aligned} Y_t &= \left[\left(A_{e,n,t} n_t^{\frac{\varepsilon-1}{\varepsilon}} + A_{e,h,t} A h_t^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}\right]^{\alpha} \left(K_{ICT}^{\sigma} K_{NICT}^{1-\sigma}\right)^{1-\alpha}, \quad (10) \\ U &= \sum_{t=1}^{3} \gamma^t \left[\ln c_t + \ln\left(1 - L \times \left(\frac{1}{B_n} u_{n,t} + \frac{1}{B_{h,t}} u_{h,t}\right)\right)\right], \quad (11) \end{aligned}$$

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 working from home,

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

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 working from home by age are given by

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

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) 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 working from home, $B_{h,t} \times A_{e,h,t}$, 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 working from home by age are given by

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

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) 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 Φ_1 and Φ_2 are from $(0,1)$ since $u_{h,t} \in (0,1)$. There are negative terms in Φ_1 and Φ_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 working from home can increase by age because of two reasons. First, it can increase if the preference for and productivity of working from home increase more than 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 Online Appendix - 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 working from home. We have performed all these robustness checks for all demographic, employment and contract type groups and have obtained results which are very similar to the results presented in the paper.

The working from home variable is from $(0, 1)$. We estimate the specification (8) 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. We also estimate the specification (8) using 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 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 (8) 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:

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

where Δ 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 working from home 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 Δ 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 (8) 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 working from home. 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 suggesting a correct identification of the effect of fall in ICT prices on working from home.

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 (8) 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. 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. 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 the 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 working from home more difficult, as children can distract from work tasks. At the same time, working from home might be desirable to facilitate the family-work balance. According to our results, a fall in ICT prices increases working from home 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 working from home. 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 information and communication technologies do not necessarily need to lead to 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 to mitigating the spread of epidemics/pandemics (Brotherhood and Jerbashian, 2020, Fadinger and Schymik, 2020). Finally, those who usually work from home might have other reasons to do so than the availability of information and communication technologies.[15] Nevertheless, we have estimated the specification (8) 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 but positive and

[15]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.

statistically significant.

We do not control for industry and year fixed effects in the the baseline specification (8). 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 working from home 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 (8). 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 marginally smaller than the baseline estimate in Table 4.

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 (8) 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 but positive and statistically significant.

D Online Appendix - 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	0.774	0.916	0.965	0.941	0.983
Young & Old	0.744	0.901	0.970	0.931	0.950
Medium-Age & Old	0.889	0.968	0.991	0.982	0.977
B. Gender					
Male & Female	0.842	0.891	0.869	0.969	0.992
C. Occupation Groups					
High & Low Wage	0.622	0.671	0.860	0.821	0.978
D. Education-Levels					
High & Medium	0.516	0.720	0.760	0.942	0.877
High & Low	0.755	0.838	0.866	0.972	0.973
Medium & Low	0.701	0.910	0.957	0.976	0.925
E. Marital Status					
Single & Married	0.913	0.953	0.983	0.961	0.997
F. Contract Type					
Temporary & Permanent	0.880	0.961	0.985	0.980	0.974
G. Tenure Length					
Short & Long	0.700	0.881	0.972	0.930	0.894
H. Children					
W & w/t Children	0.896	0.969	0.990	0.984	0.975

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	23.191	1645	0.014
Industry	7.872	11	0.716
Country	8.168	13	0.628
Industry x Country	3.422	142	0.024
Year	0.748	9	0.083
Year × Industry	0.260	99	0.003
Year × Country	1.605	115	0.014
Year × Industry × Country	1.076	1256	0.001

Note: This table reports the results from an ANOVA exercise for the working from home variable. The variation in the data are 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 9 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 are 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	12.926	1645	0.008
Industry	9.338	11	0.849
Country	0.449	13	0.035
Industry × Country	2.890	142	0.020
Year	0.012	9	0.001
Year × Industry	0.021	99	0.000
Year × Country	0.036	115	0.000
Year × Industry × Country	0.169	1256	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 are 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	2.776	137	0.020
Country	1.004	13	0.077
Year	0.706	9	0.078
Year × Country	1.089	115	0.009

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 are 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	1646	0.218	0.072	0.084	0.440	0.083
Medium	1646	0.096	0.058	0.028	0.299	0.037
Low	1627	0.058	0.043	0.005	0.201	0.023
B. Marital Status	Obs	Mean	SD	Min	Max	Δ
Single	1646	0.153	0.091	0.047	0.393	0.064
Married	1646	0.211	0.103	0.068	0.477	0.070
C. Contract Type	Obs	Mean	SD	Min	Max	Δ
Temporary	1638	0.068	0.056	0.013	0.293	0.035
Permanent/Indefinite	1646	0.132	0.075	0.033	0.393	0.069
D. Tenure Length	Obs	Mean	SD	Min	Max	Δ
Short	1646	0.110	0.070	0.023	0.343	0.060
Long	1646	0.136	0.076	0.042	0.414	0.064
E. Children	Obs	Mean	SD	Min	Max	Δ
With Children	1265	0.111	0.067	0.031	0.379	0.054
W/t Children	1265	0.086	0.055	0.018	0.294	0.035

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 9 in the Data Appendix and Table X in the Online Appendix - 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	0.864***	0.582***	0.795***
× 1/ICT Price	(0.083)	(0.084)	(0.090)
Obs	1646	1646	2641
R2 (Partial)			0.040
	D. Long Diff	*E. Long Diff w/ Interaction*	
Share of ICT Capital (2008)	0.305***		
	(0.053)		
Share of ICT Capital (2008)		0.777***	
× Δ 1/ICT Price		(0.158)	
Obs	167	167	
R2 (Partial)	0.676	0.666	

Note: This table offers the results from additional robustness check exercises. See Table 9 in the Data Appendix and Table X in the Online Appendix - Further Robustness Checks and Results for complete descriptions and sources of variables. The dependant variable is WFH in Panels $A-C$. Panels A and B report the results from the estimation of the specification (8) using Tobit$(0,1)$ and Quantile regressions. Panel C reports the results for a sample which includes Estonia, Latvia, Lithuania, and industries O, P, Q, R, S, T, and U. The dependant 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	0.320**	0.727***	0.767***	0.872***	0.943***
	(0.157)	(0.135)	(0.174)	(0.103)	(0.118)
Obs	1646	1646	1627	1646	1646
R2 (Partial)	0.002	0.039	0.014	0.042	0.055

	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	0.680***	0.872***	0.670***	0.992***	0.775***	0.584***
	(0.152)	(0.101)	(0.124)	(0.110)	(0.154)	(0.144)
Obs	1638	1646	1646	1646	1265	1265
R2 (Partial)	0.012	0.062	0.022	0.056	0.027	0.015

Note: This table offers the results from the estimation of the specification (8) 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 9 in the Data Appendix and Table X in the Online Appendix - 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.