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

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Abstract

We use data from 14 European countries and provide evidence that the fall in prices of information and communication technologies (ICT) is associated with a significant increase in the share of employees who work from home. 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. A rationale for such a result is that the preference for working from home increases with age and the benefits from working on-site decline with it.

Keywords: Working from Home; ICT; Age; Gender; Occupations

JEL classification: J23; J24; O33

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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. Meanwhile working from home has been on a steady rise for at least the last few decades in European countries and elsewhere (e.g., see Oettinger, 2011, for evidence from the US). According to the arguments of Autor (2001), the steady rise in working from home can be attributed to the rise in the use of information and communication technologies (ICT). These technologies include computers and the internet and can enable remote work.

In this paper, we empirically investigate the effect of the rapid fall in prices of ICT on working from home. We do so in a difference-in-differences framework in the spirit of Rajan and Zingales (1998). More specifically, we ask whether the fall in ICT prices has affected working from home more in industries that depend more on ICT compared to industries that depend less on ICT. We use industry- and country-level data from 14 European countries and the 2008-2016 period to establish the results.

We 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 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 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 communications 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. 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. Working from home can also be associated with increased productivity according to Bloom, Liang, Roberts, and Ying (2015). In turn, Oettinger (2011) and Mateyka, Rapino, and Landivar (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.[2] Our results complement the results of Oettinger (2011) and contribute to these studies by showing that the fall in ICT prices is associated with increased work from home especially in industries that depend more on ICT as compared to industries

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

[2] Neumark and Reed (2004) offer evidence that the growth in the new (high-tech) economy in the US is associated with an increase in contingent and alternative employment relationships.

that depend less on it.[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, 2019, 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, Falk and Koebel, 2004, Jerbashian, 2019, O'Mahony, Robinson, and Vecchi, 2008).[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

A fall in ICT prices would increase working from home more in industries that depend more on information technologies than in industries that depend less. We present a simple model to outline our assumptions and show how such an inference can hold. We also use this model 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 technologies 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

[3] Our results together with the results of Brotherhood and Jerbashian (2020) and Angelucci, Angrisani, Bennett, Kapteyn, and Schaner (2020) suggest that policies which reduce ICT prices can promote working from home and can lead to lower losses in output and employment, and fewer infections and death casualties during pandemics such as the COVID-19.

[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.

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}. 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 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:

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

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

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 (ELFS). 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. Table 1 offers the list of sample industries and their average share of working from home in Panel A. Working from home varies 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. Working from home has increased in all industries during the sample period according to the last column of Panel A.

We also retrieve information from the ELFS 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 2 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. The latter result can be justified by the preference to work from home and learning opportunities during on-site work, for example. There are no significant differences in terms of working from home between genders according to Panel C. 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 D. 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 2.

Working from home has increased by about 5 percentage points in sample countries and industries according to Figure 1 and Table 1. The establishment of this trend as a stylized fact can be considered as one of the contributions of this paper.[6]

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). The ICT 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 2008-2016 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 industry where it stands at around 27%. It is the lowest in the Real Estate industry where a large share of capital is in terms of dwellings, buildings, and other structures.

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., Gust and Marquez, 2004, 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

[6]Table I in the Appendix - Further Robustness Checks and Results shows that the pair-wise correlations of the WFH within groups are large which supports the existence of the systematic pattern and the hypothesis that there is a technological cause for changes in the WFH.

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 period 2008-2016 and the variation of the share of ICT capital in industries in the sample European 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.[7] 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 of Table 3. These observations suggest that the dependence measure used in this paper is likely to identify the technological differences across industries but not temporary shocks.[8]

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. 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).

Given data availability, the main sample includes 13 industries from 14 European countries and focuses on the period between 2008 and 2016.[9] Table 3 offers the list of countries in our sample and basic statistics for ICT Price in Panel A. ICT Price displays significant variation over time and across countries (see also Table IV in the Appendix - Further Robustness Checks and Results). 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.

[7] Table II and Table III report these results in the Appendix - Further Robustness Checks and Results.

[8] 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.

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

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:

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

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 result in comparative static (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 regulatory and discriminatory practices that affect 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 that are not different across industries. In such a case, this test can be also viewed as a test of whether 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.

One way we can quantify these results and show their economic significance is as follows. We compute the average change in 1/ICT Price between 2008 and 2016 in the sample countries (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 0.014. 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 0.031. 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.[10]

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 learning opportunities from on-site work across age groups can be the explanation for 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

[10] According to Table IV in the Appendix - Further Robustness Checks and Results, the country-level variation in ICT prices is as important as yearly and country-year-level variation. This can be suggesting that there is a room for policies that affect ICT prices and, subsequently, can have large effects on working from home.

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 almost the same as and statistically not distinguishable from the effect on working from home among medium-age 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.[11]

In an attempt 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 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 rule out 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 appro-

[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 Appendix - Further Robustness Checks and Results.

priate 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 about twice 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 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 does not change. In turn, the estimate of the coefficient on the newly added term is insignificant. This suggests that general structural changes such as the substitution of capital for labor are not likely to play a role in changes in working from home.

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 D of Table 7. 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.

Next, we check the robustness of our results by dropping potential outliers from the sample. First, there is a large variation in ICT prices across countries according to Table 3. 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 E of Table 7 shows that dropping these countries from the sample does not significantly affect our results. Second, the trends in working from home in some industries in Luxembourg and Sweden, and the levels of working from home in the Netherlands in 2015 and 2016 seem to be considerably larger than the within country average. In Panel F we drop from the sample Luxembourg, Sweden and data for the Netherlands from 2015 and 2016. Again, these sample restrictions do not affect our main results in a statistically significant way. Third, 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 G. 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 and above within each country to further exclude potential outliers. Panel H offers the results with trimmed data. These results are almost identical to the baseline results.[12]

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 2016. The 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

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

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. Our findings also suggest that policies that reduce ICT prices can promote working from home.

6 Tables and Figures

Table 1: Working from Home in Sample Industries and ICT Dependence

		A. Working from Home						*B. ICT Dependence*
Industry Name	Industry Code	Obs.	Mean	SD	Min	Max	Δ	ICT Dependence
Agriculture, Forestry and Fishing	A	117	0.112	0.097	0.000	0.449	0.020	0.002
Mining and Quarrying	B	117	0.091	0.146	0.000	1.000	0.043	0.006
Manufacturing	C	117	0.089	0.069	0.009	0.274	0.055	0.035
Electricity, Gas and Steam Supply	D	117	0.150	0.131	0.000	0.671	0.106	0.008
Water supply and Sewerage	E	117	0.078	0.068	0.000	0.263	0.054	0.015
Construction	F	117	0.074	0.055	0.002	0.228	0.046	0.033
Wholesale and Retail Trade; Repair of Vehicles	G	117	0.084	0.058	0.007	0.238	0.044	0.070
Transportation and Storage	H	117	0.062	0.045	0.003	0.234	0.037	0.031
Accommodation and Food Services	I	117	0.038	0.029	0.001	0.162	0.024	0.012
Information and Communication	J	117	0.295	0.169	0.032	0.623	0.137	0.244
Financial and Insurance Activities	K	117	0.170	0.117	0.011	0.624	0.114	0.128
Real Estate Activities	L	117	0.171	0.115	0.000	0.581	0.051	0.001
Professional and Support Service Activities	M-N	117	0.166	0.107	0.008	0.406	0.079	0.173

Note: Panel *A* of this table offers the descriptive statistics of working from home in sample industries. 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) in sample industries. See Table 8 in the Data Appendix for complete descriptions and sources of variables.

Table 2: Working from Home within Gender, Age, and Occupation Groups

A. Age Groups	Obs	Mean	SD	Min	Max	Δ
Young	1630	0.075	0.048	0.015	0.248	0.049
Medium-Age	1635	0.142	0.078	0.044	0.399	0.068
Old	1635	0.128	0.073	0.04	0.383	0.061
B. Gender	Obs	Mean	SD	Min	Max	Δ
Male	1637	0.130	0.081	0.034	0.381	0.058
Female	1631	0.121	0.059	0.027	0.327	0.079
C. Occupation Groups	Obs	Mean	SD	Min	Max	Δ
High	1632	0.216	0.055	0.111	0.405	0.085
Low	1636	0.053	0.032	0.014	0.157	0.035

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. See Table 8 in the Data Appendix for complete descriptions and sources of variables.

Table 3: Sample Countries, 1/ICT Price and Correlations with ICT Dependence

	A. Basic Statistics for 1/ICT Price					*B. Correlations*
Country	Mean	SD	Min	Max	Δ	ICT Dependence
Austria	1.098	0.083	0.991	1.226	0.235	0.852
Czechia	1.012	0.024	0.977	1.051	0.055	0.842
Denmark	1.056	0.074	0.951	1.194	0.242	0.795
Finland	1.124	0.153	0.847	1.337	0.490	0.616
France	1.210	0.232	0.878	1.526	0.648	0.947
Germany	1.043	0.049	0.961	1.103	0.142	0.924
Italy	0.974	0.024	0.944	1.017	-0.066	0.880
Luxembourg	1.034	0.032	0.990	1.093	0.064	0.902
Netherlands	1.033	0.073	0.877	1.131	0.255	0.907
Slovakia	0.999	0.024	0.938	1.023	-0.068	0.838
Slovenia	1.083	0.083	0.962	1.205	0.189	0.864
Spain	1.037	0.058	0.930	1.124	0.195	0.961
Sweden	1.264	0.231	0.924	1.553	0.461	0.770
UK	1.024	0.070	0.908	1.128	-0.220	0.871

Note: Column 1 of this table lists sample countries. The sample period is 2008-2016. Panel *A* offers basic statistics for the inverse of the price of information technologies (1/ICT Price). Column 5 of Panel *A* offers the change in 1/ICT Price over the sample period in each country (Δ). Panel *B* offers the pairwise correlations of the measure of dependence on information technologies (ICT Dependence) and the shares of ICT capital share in the industries of the sample European countries. All correlations are significant at least at the 5% level. See Table 8 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	0.737*** (0.109)
Obs	1638
R2 (Partial)	0.022

B. The Magnitude of the Predicted Effect

$\hat{\beta} \times \Delta 1/\text{ICT Price} \times \Delta\text{ICT Dependence}$	0.014
$(WFH_{HD,2016} - WFH_{HD,2008}) - (WFH_{LD,2016} - WFH_{LD,2008})$	0.031
Predicted Effect, % of actual	45.486

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, $\big(WFH_{HD,2016} - WFH_{HD,2008}\big) - \big(WFH_{LD,2016} - WFH_{LD,2008}\big)$, and the percentage of the explained variation by the fall in ICT prices. Δ1/ICT Price is the average of Δ in Table 3. 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. 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 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 5: Results for Age, Gender, and Occupation Groups

	Age Groups		
	A. Young	*B. Medium-Age*	*C. Old*
ICT Dependence x 1/ICT Price	0.352***	0.622***	1.001***
	(0.128)	(0.131)	(0.128)
Obs	1630	1635	1635
R2 (Partial)	0.003	0.011	0.043

	Gender		Occupation Groups	
	D. Male	*E. Female*	*F. High Wage*	*G. Low Wage*
ICT Dependence x 1/ICT Price	0.766***	0.437***	0.613***	0.611***
	(0.120)	(0.162)	(0.129)	(0.121)
Obs	1637	1631	1632	1636
R2 (Partial)	0.022	0.004	0.009	0.021

Note: This table offers the results from the estimation of the specification (8) 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 $\times$ 1/ICT Price	0.323**	0.767***	0.907***
	(0.143)	(0.179)	(0.191)
Obs	1630	1629	1626
R2 (Partial)	0.002	0.010	0.013
	Age Groups - Married		
	E. Young	*F. Medium-Age*	*G. Old*
ICT Dependence $\times$ 1/ICT Price	0.736*	0.620***	0.998***
	(0.379)	(0.174)	(0.145)
Obs	1537	1632	1634
R2 (Partial)	0.003	0.007	0.032

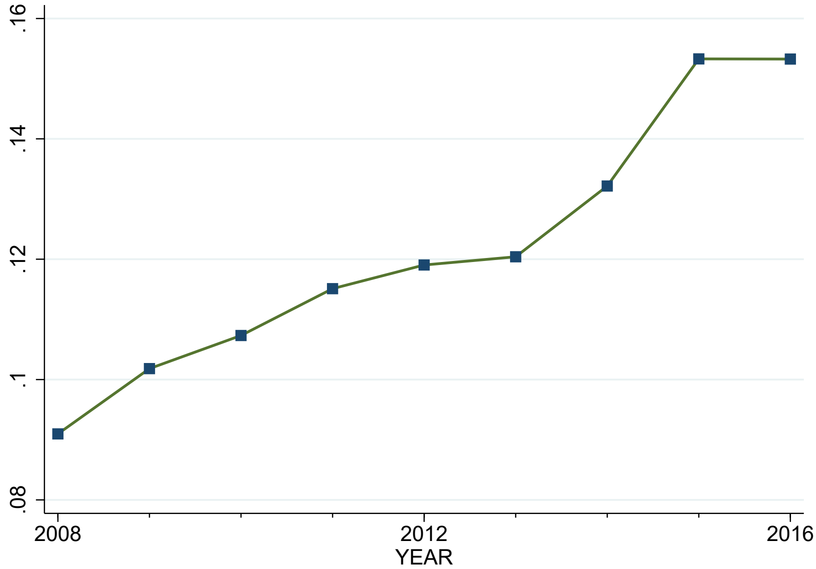
Note: This table offers the results from the estimation of the specification (8) for the WFH computed within age and marital status groups. See Table 8 in the Data Appendix for complete descriptions and sources of variables. All regressions include country-industry and country-year dummies and use the 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 - Measures, Additional Variables, and Sample Restrictions

	A. ICT Dependence (2008)	*B. Share of ICT Capital*	*C. Capital Dependence*	*D. W/o High ICT Using*
ICT Dependence	0.720***		0.734***	0.631***
× 1/ICT Price	(0.109)		(0.105)	(0.176)
Share of ICT Capital		0.334***		
× 1/ICT Price		(0.068)		
Capital Dependence			-0.013	
× 1/Capital Price			(0.022)	
Obs	1638	1620	1620	1368
R2 (Partial)	0.022	0.015	0.024	0.006
	E. W/o CZ, IT, LU, SK, UK	*F. W/o LU, SE, NL 2015, 2016*	*G. W/o J and K*	*H. Trimmed*
ICT Dependence	0.795***	0.578***	0.321**	0.704***
× 1/ICT Price	(0.110)	(0.123)	(0.133)	(0.106)
Obs	1053	1378	1386	1590
R2 (Partial)	0.062	0.043	0.002	0.033

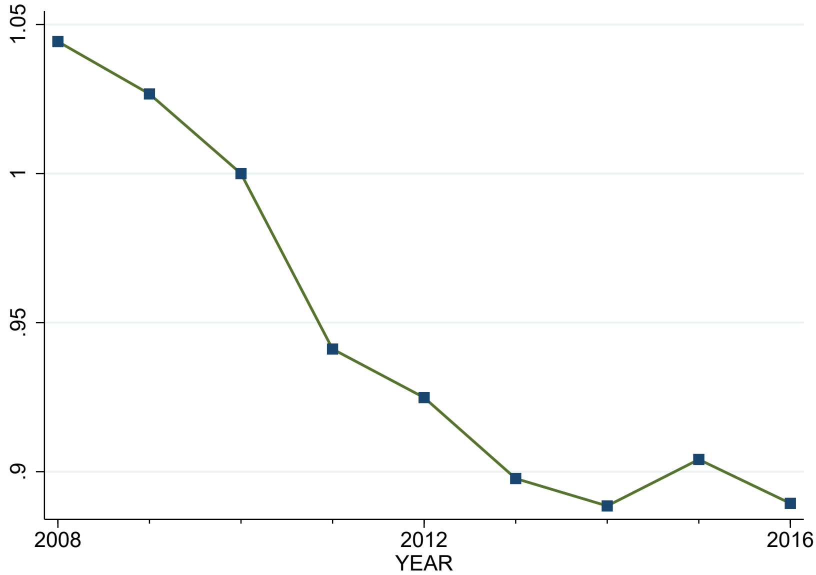
Note: This table offers the results from robustness check exercises. The dependant variable is WFH. Panels *A* and *B* offer the results from the estimation of the specification (8) using ICT Dependence (2008) and Share of ICT Capital as the dependence measures. Panel *C* offers the results from the estimation of an augmented version of the specification (8) which has an additional interaction term. The number of observations is 1620 in panels *B* and *C* since the Share of ICT Capital and the non-ICT capital dependence measure have a lower number of observations. In Panel *D*, 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. We exclude from the sample Czechia, Italy, Luxembourg, Slovakia, and the UK in Panel *E*. We exclude Luxembourg, Sweden, and data from the Netherlands for 2015 and 2016 in Panel *F*. Industries *J* and *K* are excluded from the sample in Panel *G*. Finally, we trim the data for working from home within each country to exclude potential outliers. Panel *H* 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



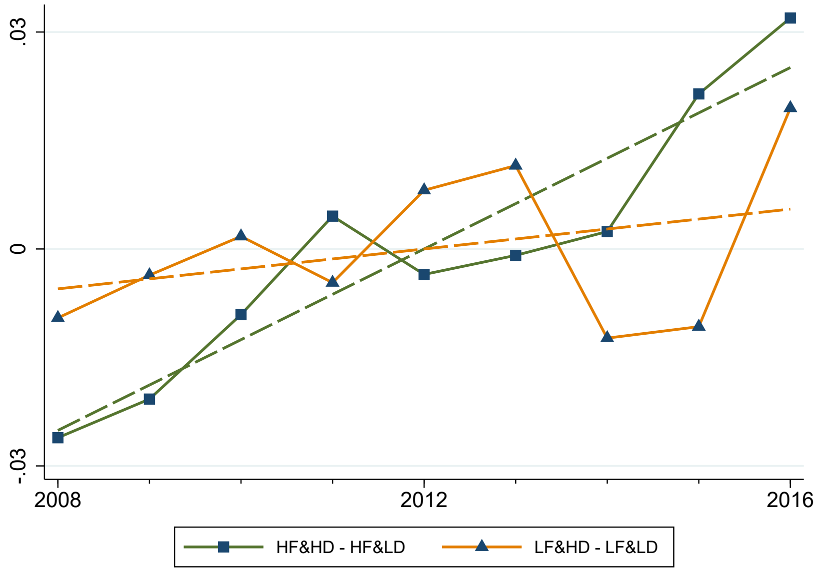
Note: This figure illustrates the trends in the WFH which is averaged across sample industries and countries. See 8 in the Data Appendix complete descriptions and sources of variables.

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



Note: This figure illustrates the evolution of the price of information and communication technologies 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.

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 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
ICT Dependence	The share of ICT capital in total capital in US industries averaged over the 2008-2016 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.
Capital Dependence	The ratio of physical capital and value added in US industries averaged over the 2008-2016 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 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.
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 individuals older than 65 for computing this measure. Source: Authors' calculations using data from EU LFS.
Share of ICT Capital	The share of ICT capital in total capital in sample industries, countries, and years. Authors' calculations using data from EU KLEMS.
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).

Table 8 – (Continued)

Variable Name	Definition and Source
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: December 2015 release of the EU Labour Force Survey database; November 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: 2008-2016.

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B 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

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

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

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

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

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

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 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 VI. 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 VI. The estimate on the coefficient is somewhat lower but not statistically different from the baseline estimate.

Our data also contain information from small 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 VI. 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 2016 and 2008 values, $\tilde{\xi}$ 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 2016 and 2008 values, $\hat{\xi}$ 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 VI 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 ELFS 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 ELFS: 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 VII. 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 VII 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 VII 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.

D Appendix - Tables and Figures

Table I: Correlations of Working from Home within Demographic, Employment and Contract Type Groups

A. Age Groups	Industry-Country-Year	Industry-Country	Industry	Country	Year
Young & Medium-Age	0.935	0.960	0.893	0.743	0.972
Young & Old	0.911	0.966	0.838	0.695	0.965
Medium-Age & Old	0.981	0.987	0.943	0.883	0.983
B. Gender					
Male & Female	0.750	0.829	0.771	0.974	0.980
C. Occupation Groups					
High & Low Wage	0.624	0.668	0.849	0.815	0.953
D. Education-Levels					
High & Medium	0.756	0.861	0.879	0.954	0.980
High & Low	0.528	0.757	0.791	0.933	0.899
Medium & Low	0.715	0.879	0.918	0.973	0.950
E. Marital Status					
Single & Married	0.888	0.937	0.981	0.960	0.988
F. Contract Type					
Temporary & Permanent	0.677	0.875	0.978	0.930	0.825
G. Tenure Length					
Short & Long	0.852	0.953	0.987	0.986	0.933
H. Children					
W & w/t Children	0.838	0.959	0.988	0.985	0.939

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 the Share of ICT Capital in US Industries

Source	Partial SS	df	MS
Total	0.635	116	0.005
Industry	0.632	12	0.053
Year	0.001	8	0.000
Year × Industry	0.002	96	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 2008-2016 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 III: ANOVA for the Share of ICT Capital in Industries of Sample European Countries

Source	Partial SS	df	MS
Total	12.018	1619	0.007
Industry	8.678	12	0.723
Country	0.393	13	0.030
Industry × Country	2.756	154	0.018
Year	0.006	8	0.001
Year × Industry	0.016	96	0.000
Year × Country	0.024	104	0.000
Year × Industry × Country	0.142	1232	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 IV: ANOVA for ICT Price

Source	Partial SS	df	MS
Total	2.273	125	0.018
Country	0.769	13	0.059
Year	0.613	8	0.077
Year × Country	0.890	104	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 V: Working from Home within Demographic, Employment and Contract Type Groups

A. Education-Level	Obs	Mean	SD	Min	Max	Δ
High	1631	0.212	0.068	0.084	0.411	0.075
Medium	1633	0.093	0.055	0.026	0.289	0.042
Low	1612	0.056	0.040	0.004	0.200	0.028
B. Marital Status	Obs	Mean	SD	Min	Max	Δ
Single	1634	0.147	0.087	0.040	0.389	0.062
Married	1636	0.201	0.101	0.063	0.443	0.070
C. Contract Type	Obs	Mean	SD	Min	Max	Δ
Temporary	1617	0.066	0.052	0.013	0.253	0.042
Permanent/Indefinite	1638	0.128	0.072	0.032	0.374	0.066
D. Tenure Length	Obs	Mean	SD	Min	Max	Δ
Short	1632	0.106	0.066	0.023	0.330	0.058
Long	1638	0.132	0.073	0.041	0.386	0.064
E. Children	Obs	Mean	SD	Min	Max	Δ
With Children	1260	0.106	0.062	0.031	0.33	0.049
W/t Children	1258	0.084	0.052	0.018	0.268	0.034

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 VIII in the Appendix - Further Robustness Checks and Results for complete descriptions and sources of variables.

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

	A. Tobit	*B. Quantile*	*C. All*
ICT Dependence	0.733***	0.519***	0.694***
$\times$ 1/ICT Price	(0.087)	(0.091)	(0.095)
Obs	1638	1638	2592
R2 (Partial)			0.017

	D. Long Diff	*E. Long Diff w/ Interaction*
Share of ICT Capital (2008)	0.262***	
	(0.042)	
Share of ICT Capital (2008)		0.657***
$\times\Delta$ 1/ICT Price		(0.146)
Obs	180	180
R2 (Partial)	0.123	0.088

Note: This table offers the results from additional robustness check exercises. See Table 8 in the Data Appendix and Table VIII in the 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 VII: 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	0.355**	0.654***	0.615***	0.719***	0.828***
	(0.147)	(0.140)	(0.182)	(0.119)	(0.117)
Obs	1631	1633	1612	1634	1636
R2 (Partial)	0.002	0.020	0.008	0.017	0.026
Obs	1613	1615	1594	1616	1618
R2 (Partial)	0.002	0.020	0.008	0.017	0.026

	Contract Type		Length of Tenure		Children	
	F. Temporary	*G. Permanent*	*H. Short*	*I. Long*	*J. With Children*	*K. W/o Children*
ICT Dependence × 1/ICT Price	0.466***	0.757***	0.556***	0.844***	0.636***	0.445***
	(0.147)	(0.104)	(0.134)	(0.121)	(0.159)	(0.170)
Obs	1617	1638	1632	1638	1260	1258
R2 (Partial)	0.004	0.022	0.010	0.024	0.010	0.005

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 8 in the Data Appendix and Table VIII in the 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 VIII: 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.