When does remote electronic access (not) boost productivity? Longitudinal evidence from Portugal*

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Abstract

Whether or not the option to work remotely increases firm labour productivity is theoretically ambiguous. We use a rich and representative sample of Portuguese firms, and within-firm variation in the policy of remote electronic access – a key prerequisite for remote work – over the period 2011-2016, to empirically assess the relationship between remote access and firm labour productivity. Based on estimations of models with firm-fixed effects, we find a significantly negative association, on average, between remote access and productivity. However, we also find a substantial degree of heterogeneity across different categories of firms, where the association between remote access and productivity is significantly positive for firms that undertake R&D activities. Our findings suggest that the possibility of working remotely, as proxied by the possibility of remote access, is more likely to be harmful for productivity in non-exporting, small firms that do not do R&D, and that employ a workforce with a below-average skill level.

Keywords: Remote access; firm labour productivity; panel data.

JEL Classification: D24; L23; M54.

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1 Introduction

In recent years, with the widespread use of cloud services and remote access to work applications, workers can perform their tasks outside the office (OECD, 2016). This provision of 'remote work' thus allows workers to perform what is often referred to as 'telework' or 'telecommuting'. In 2015 in the US, nearly 4 million workers (representing 3 percent of the workforce) worked at least half of their time away from the office (GWA, 2017), and in the EU those who usually work from home constituted 5 percent of the employed workers (Eurostat, 2018).

This trend, driven mainly by the digital revolution, has been changing the workplace organisation in a number of ways. Teleworkers may work at home but also turn to coffee shops or co-working spaces, or even travel around the world while maintaining their career goals. Video conferencing allows out-of-office workers to communicate and interact with each other in real time anywhere they are. Telework today also encompasses various full-time jobs in a wide set of occupations (not only highly educated) across multiple industries.

Technological advances in how work is performed may mean that 'anywhere working' becomes business-as-usual (Blount, 2015). In the US, 70 percent of firms surveyed by the Society for Human Resource Management allowed telecommuting from an ad-hoc to a full-time basis (SHRM, 2018). Furthermore, around 75 percent of Europeans have access to some flexibility in their work in terms of schedule and location, and this is advocated as allowing better management of work and family life (OECD, 2016; Eurofound, 2017). To such end, the Work-Life Balance Directive (EU, 2019) was adopted in August 2019 by the European Parliament to allow parents and carers the right to remote work arrangements. Of course, the exceptional circumstances brought about by the COVID-19 pandemic in 2020 have strongly reinforced the trend of remote work and highlighted the health and safety advantages of such arrangements for firms where required social distancing at the workplace is not possible.

How does this global trend affect workplace performance? Do more flexible workplace arrangements translate into mutual benefits to both employees and employers? While anecdotal evidence might point to several advantages of remote work (to workers and firms alike), the existing empirical evidence on the effects of teleworking is less conclusive. In particular, an extensive body of work shows mixed evidence on the linkages between out-of-office work and various individual-level worker outcomes (such as turnover, job autonomy and satisfaction, and motivation).[1] Regard-

[1] See for example the surveys by Bailey and Kurland (2002), Gajendran and Harrison (2007) and Allen et al.

ing the effect on productivity (at worker or firm level), whereas the empirical evidence generally points to a positive effect of remote work, recent lab experiments provide evidence of negative or, at best, mixed effects of telework on productivity. Novel theoretical developments also show that the relationship between self-managed working time (which includes remote work), employee effort, and thus worker productivity, is not unambiguously positive, as commonly derived in various approaches from economics and related fields.[2]

In the present paper, we contribute to the literature on remote work and productivity by empirically analysing the effect of a key prerequisite for the possibility of working remotely, namely *remote electronic access*. More specifically, we study how the possibility of remote access affects firm labour productivity, as measured by sales per worker, using firm-level data for Portugal, a country where the prevalence of telecommuters is higher than the EU-28 average. We conduct our analysis by first gathering information from the *Community Survey on ICT Usage and E-Commerce in Enterprises* (Eurostat, 2011) during the 2011-2016 period, which contains the following question: 'Did your enterprise provide to the persons employed remote access to the enterprise's e-mail system, documents and applications?'. This survey is then matched with data from the Portuguese *Integrated Business Accounts System* to recover data on firm characteristics, allowing us to build a panel covering the years 2011, 2012, 2013 and 2016.

A potentially important caveat for the interpretation of the results from this analysis is that we only observe whether or not workers in a firm are given remote electronic access. We do not observe whether there are any formal remote work arrangements in place, or the share of workers actually working remotely. Nevertheless, since in most cases remote access to e-mail, documents and applications is both a necessary and sufficient condition for working remotely, it seems reasonable to interpret the enablement of remote access as a proxy for remote work enablement, i.e., whether or not the firm allows (at least some of) their employees to work from home.

The main contribution of our analysis is related to the nature and richness of our data, which allows us to study the impact of firms' remote access policies across a wide range of firms and industries. This is in contrast to much of the existing literature that has looked at non-random or selected samples, usually large firms and in manufacturing.[3] Importantly, the richness of the data enables us to analyse the possibility of *heterogeneous effects* of remote access along several different

(2015).

[2] A review of the related empirical and theoretical literature is given in Section 2.

[3] One exception is Viete and Erdsiek (2020) who study the potential existence of complementarities between mobile ICT and trust-based work time arrangements in German service firms.

dimensions related to firm, worker and job characteristics. In turn, this allows us to draw some conclusions regarding in which cases a policy of allowing remote access is likely to have a positive effect on firm labour productivity, and in which cases remote access is likely to be detrimental to productivity. Furthermore, the panel structure of the dataset improves upon the majority of empirical studies that are based on cross-sectional data. In particular, this feature combined with the within-firm variation in remote access policy allows us to control for firm-fixed heterogeneity, which in turn enables us to circumvent some potentially important endogeneity issues.

Our empirical strategy consists of estimating an augmented Cobb-Douglas production function on several firm characteristics, which is a standard approach in the literature (e.g., Black and Lynch, 2004; Bloom et al., 2011, 2019). The effect of remote access on labour productivity is identified by a difference-in-differences estimator comparing the differences in productivity trends between two categories of firms: (i) those that changed their policy on remote access during the period of analysis (either adopting or abandoning such a policy), and (ii) those that always had the same remote access policy in place (either allowing it or not).[4]

As a starting point and benchmark for comparison, we estimate the empirical model on the full sample of firms, finding a significantly negative association between remote access and firm labour productivity on average. However, our subsequent analysis reveals that this average association masks a considerable degree of heterogeneity. More specifically, we find that the negative association between remote access and productivity is mainly present for small and non-exporting firms, which do not perform any R&D activities and employ a workforce with a below-average skill level. On the other hand, for the subcategory of firms that undertake some R&D activities, we find a significantly *positive* association between remote access and labour productivity. The finding of significantly opposite associations between remote access and productivity depending on the R&D status of the firm, which is one of the key results in our paper, has intriguing parallels to previous experimental evidence showing that remote work affects productivity differently for 'routine' versus 'creative' job tasks (Dutcher, 2012).

Another interesting feature of our results is that the inclusion of a firm-fixed effect in the empirical model makes a crucial difference. In our benchmark model using the full sample, the estimation of a specification without firm-fixed effects yields a positive relationship between remote

[4] Notice that this identification strategy, which is based on firms that change policy, is different from the identification strategy used in related studies based on individual-level panel data, where identification is based on workers who move between firms with different policies in place (e.g., Kröll and Nüesch, 2019).

access and labour productivity, although this association ceases to be statistically significant if we control for the full set of worker and firm characteristics. However, once we control for time-invariant firm-level heterogeneity, the sign of our key estimate reverses, indicating a significantly negative association between remote access and firm labour productivity on average. This result is particularly noteworthy in the light of the fact that a large portion of the existing empirical literature on remote work, often presenting a positive relation, is based on cross-sectional evidence.

The remainder of the paper is organised as follows. In Section 2 we review the relevant theoretical and empirical literature. We proceed in Section 3 by presenting the data and variables, including descriptive statistics, before introducing and discussing our empirical strategy in Section 4. The analysis based on the full sample of firms, including several robustness checks, is given in Section 5. In Section 6 we explore the possibility of inter-firm heterogeneity by re-estimating our preferred empirical model on a number of subsamples defined according to several relevant partition criteria. Finally, Section 7 closes the paper with some concluding remarks.

2 Background and related literature

In this section we provide a relatively brief review of the related literature. As previously discussed, our analysis of the effect of remote electronic access on firm labour productivity relies on the underlying assumption that remote access serves as a proxy for the existence of remote work arrangements, which implies that the relevant literature consists of theoretical or empirical studies linking remote work and productivity. We review this literature in two steps. First, we present some key theoretical mechanisms, suggested by different strands of the literature, that could help explain a potential relationship between remote work and firm labour productivity. Subsequently, we present an overview of the available empirical evidence of such a relationship.

2.1 Theory

So far, no theoretical work has explicitly modelled the linkage between remote work and productivity (or other measures of firm performance). Past empirical research has borrowed various arguments and mechanisms from different strands of economics and related fields to explain the referred linkage. In particular, remote work has been framed (i) in the context of reciprocal gift exchange following Akerlof (1982); (ii) under the efficiency wage model of Akerlof and Yellen (1988); (iii) as part of high-performance work practices that transfer power to workers following the rent-sharing model of Freeman and Lazear (1994); (iv) as a strategic management practice to increase psychological well-being and motivation of workers, e.g., Bloom et al. (2011) and Bloom and Van Reenen (2011); or (v) as an expression of corporate social responsibility, e.g., Fauver et al. (2018).

Akerlof (1982)'s model concerns reciprocity and the employer-employee relation is viewed as a type of gift exchange. Workers who are paid above market-clearing wage develop a sentiment for their managers and reciprocate the gift by working harder (e.g., Falk and Fischbacher, 2006). Extending the compensation to consider remote work or other non-pecuniary incentives, this view predicts higher exerted effort by workers and increased firm performance in exchange for higher worker compensation.

Under the efficiency wage framework (Akerlof and Yellen, 1988), the argument is in the same vein. Firms pay wages above market-clearing levels to make it more costly for workers to switch jobs and thus reduce turnover. Furthermore, the fair wage-effort argument of Akerlof and Yellen (1990) implies that workers reduce their effort if rewarded below a certain value deemed fair and conversely increase effort if rewarded above that benchmark. The argument can thus include non-monetary incentives such as more flexible time management and family-friendly practices.

The model of rent-sharing by Freeman and Lazear (1994) in the context of works councils within firms has also been extended to include remote work or any other high-performance work practice (e.g., Cappelli and Neumark, 2001; Black and Lynch, 2004). Works councils have 'rights to information and consultation about labor and personnel decisions' (Freeman and Lazear 1994, p. 29) and can potentially increase the power of workers within firms, leading to an increase in workers' share of total economic rents and potentially an increase in those rents. Up to a point, this is possible without reducing performance. As highlighted by Cappelli and Neumark (2001, p. 738), 'in the context of this model, we can think of innovative work practices as potentially acting like works councils, possibly increasing productivity, but also likely increasing labor costs, with ambiguous implications for unit labor costs (and profitability)'.

Another argument for the hypothesis of a positive impact of remote work on firm productivity concerns workers' psychological well-being and motivation (OECD, 2007). Remote work consists of one possible strategic management practice implemented to promote a family-friendly culture within the firm. The promotion of such a culture allows workers to better manage the so called 'work-family conflict' leading to increased job motivation and satisfaction, which in turn helps firms in recruitment and retention of talented or high-ability workers. Remote work can thus lead to increased firm productivity through individual channels (see, e.g., Beauregard and Henry, 2009; Bloom et al., 2011; Bloom and Van Reenen, 2011; Edmans, 2012; Allen et al., 2015). On the other hand, there might also be counter-arguments related to the effect of remote work through the psychological well-being of workers. For example, Sonnentag and Bayer (2005) document how the inability to psychologically detach from work ('switching off' mentally) can have negative health effects on workers. To the extent that remote work makes such psychological detachment more difficult, this could ultimately have negative effects on productivity. See also Boswell and Olson-Buchanan (2007) for a related study.

Finally, the promotion of employee- and family-friendly work practices can be an expression of corporate social responsibility, and the debate about the value creation of corporate social responsibility is still ongoing. On the one hand, it allows firms to take a longer-term perspective on their activities and in doing so maximise profits in the long term rather than in the short term (Bénabou and Tirole, 2010). On the other hand, an employer that signals prosocial concerns by for example offering higher wages and other work benefits may receive in return more productivity from motivated workers (Ellingsen and Johannesson, 2008; Beckmann et al., 2017).

While these arguments are mostly in favour of the positive impact hypothesis, several other channels exist through which remote work can negatively influence worker and firm performance. Therefore, while allowing for remote work can be good for workers, it is possible that this does not translate into value creation for the firm. The earlier mentioned increase in labour costs is one such channel (Cappelli and Neumark, 2001). Furthermore, the agency theory of the firm proposes that managers will not always make value creating decisions (Jensen and Meckling, 1976), including human resource management (e.g., Pagano and Volpin, 2005), which might counter the argument related to corporate social responsibility. Additionally, remote work reduces the possibility of peer effects and team work (Elsbach et al., 2010). More importantly, there is a perception of a loss of control by employers of workers' effort, which may allow shirking and reduce performance (Felstead et al., 2003), and this mechanism is further reinforced when viewing the employer-employee relation as a principal-agent relation, where goals are not aligned, in particular when effort cannot be observed.

The model of Beckmann et al. (2017) captures what appears to be a key trade-off involved in a firm when remote work is introduced, namely the potential benefits for the firm in terms of intrinsic motivation of workers and reciprocal effort versus the cost of the loss of control. The model considers self-management of time by workers, which under an imprecise monitoring of effort, can lead to lower productivity. This effect is however counteracted by intrinsic motivation of workers. Consequently, the net effect on worker effort, and in turn firm productivity, is *a priori* ambiguous. Furthermore, the relative magnitudes of the costs and benefits involved in this trade-off is likely to differ across different types of jobs, firms and industries, which in turn suggests that there might be heterogeneous productivity effects of remote work. We return to a more elaborate discussion of this in Section 6.

2.2 Empirical evidence

Although there is a rich (and multidisciplinary) literature on various aspects and effects of remote work, the empirical evidence concerning the relationship between remote work and objective measures of productivity (or other types of performance measures) is relatively scarce.[5] Perhaps the most solid evidence to date of such a relationship is provided by Bloom et al. (2015), who find a significantly positive impact of remote work in a field experiment within a single firm (a travel agency call centre in China) using objective individual-productivity measures. Workers, after opting into the possibility to work at home and fulfilling qualifying conditions, were randomly assigned to either work from home or in the office. After a nine-month period, the company experienced an increase in several productivity measures (number of calls made and minutes worked per shift).

The remaining empirical evidence consists mainly of studies analysing the effects of remote work within the context of multiple human resource management practices, which are typically summarised in one or more firm-level indices and therefore makes it difficult to attribute the estimated effect to remote work in isolation.[6] However, some of these studies also report partial effects of individual management practices, including remote work arrangements. For example, Meyer et al. (2001) find a positive correlation between the share of workers working from home and firm performance, measured by profits, based on non-representative US data. In a later study, Martínez-Sanchez et al. (2008) report a similar result for a small sample of Spanish firms. More recently, Whyman et al. (2015) also find a positive relationship between remote work and firm performance (measured by financial turnover) using UK data, but this relationship only appears

[5] As noted in the survey by Bailey and Kurland (2002), most studies on productivity effects of remote work rely on subjective (self-reported) productivity measures.

[6] Firm-level indices are computed either by summing up the number of human resource management practices or by factor analysis decomposition. See, e.g., Huselid (1995), Ichiniowsky et al. (1997), Konrad and Mangel (2000), Bloom and Van Reenen (2007), Bloom et al. (2011) and Fauver et al. (2018).

for non-unionised firms. In contrast to the previously mentioned studies, Whyman et al. (2015) measure remote work as the *possibility* to work from home and not as the actual share of remote workers. In this sense, it is more similar to our study (although we only observe remote access as a proxy for the possibility of remote work).

The above referred empirical evidence generally suggests that remote work has a positive effect on productivity or firm performance. On the other hand, evidence from lab experiments points to ambiguous, and potentially adverse, productivity effects of remote work. For example, Dickinson and Villeval (2008) show that, up to a certain level, increased monitoring of agents by principals in a work relation increases the agent's effort, which implies that the lower control implied by remote work would decrease productivity. Additionally, remote work can reduce the possibility of synergies and peer effects, as well as the advantages of team work, including spillover effects from high-performing workers on other workers, as documented by Mas and Moretti (2009). Results from the experimental literature also suggest that the effects of remote work on individual productivity might depend on the type of tasks performed. In a set-up with two distinctly different types of tasks – 'dull' and 'creative' – Dutcher (2012) finds that remote work (i.e., the out-of-lab environment) leads to higher productivity in the creative task but lower productivity in the dull task. In a more recent web-based experiment, Brüggen et al. (2019) observe that, after controlling for self-selection of workers into remote work, there is no effect of remote work on individual productivity.

A common feature of the empirical literature on remote work and firm productivity (or performance) is that heterogeneous effects (across jobs, firms and industries) are generally not explored. The only exception is Whyman et al. (2015) who find different effects depending on whether firms are unionised or not. Thus, our main contribution to the existing literature arguably lies in our analysis of heterogeneous productivity effects of remote access. In this vein, our paper can be seen as an empirical exploration of the implications suggested by the experimental evidence of Dutcher (2012), where the distinction between 'dull' and 'creative' tasks is extrapolated to different types of firms and industries. This extrapolation will be further discussed in Section 6.

3 Data and descriptive statistics

Our data combine information drawn from two panel datasets provided by the Portuguese National Institute of Statistics (INE): *Inquérito à Utilização de Tecnologias de Informação e da Comunicação nas Empresas* (IUTIC) and *Sistema de Contas Integradas das Empresas* (SCIE). IUTIC is a yearly survey conducted since 2004 that gathers information on the use of information and communication technologies and e-commerce in enterprises. This is part of the *Community Survey on ICT Usage and E-Commerce in Enterprises* by Eurostat (2011). In Portugal, this survey is a census for large firms (with more than 250 workers or total revenues larger than 25 million euros), whereas for the remaining firms, it consists of a stratified random sample based on the size of revenues and industry affiliation.[7] The survey is compulsory by law for the selected firms located either in the mainland or in the Azores and Madeira archipelago regions.

Importantly for our purposes, the survey asks if the firm offers workers the possibility of remote electronic access. More specifically, we survey includes the following question: 'Did your enterprise provide to the persons employed remote access to the enterprise's e-mail system, documents and applications?'. We interpret the answer to this question as a proxy for remote work enablement by the firm. This question is only available in 2011, 2012, 2013 and 2016. These years thus define the time span of our main analysis. The IUTIC survey also allows us to build other related variables needed for our empirical analysis, including the share of workers who use a personal computer (PC) at least once per week.

An important caveat here is that the survey question refers to remote access and not explicitly to remote work, which means that we cannot rule out the possibility that remote access does not always imply that the firm has a formal home-working arrangement in place. Nevertheless, since in most cases remote access to e-mail, documents and applications is both a necessary and sufficient condition for working remotely, it seems reasonable to consider the frequency of positive answers to the survey question as a proxy for the frequency of firms that allow remote work.[8]

The IUTIC survey is an unbalanced panel where the number of observations ranges from 5227 in 2011 to 6574 in 2016. We match IUTIC firm-level data with data from SCIE, which is an annual census for any entity that produces goods or services in a given year, in any economic sector, regardless of its size. As both datasets include the same unique firm identifiers, we are able to trace firms over time and conduct a panel data analysis.

[7] The survey includes firms with at least one employee but excludes firms with Sole Proprietorship as the legal status.

[8] As a tentative validation test of this interpretation, we have calculated an upper bound on the share of workers in our dataset who could potentially work from home if remote access is a reasonable proxy for remote work enablement. We have done this by interacting the proxy with the share of workers in each firm who use a PC (at least once per week). During the period of analysis, this gives an upper bound of 31-35 percent. If we compare this with information from Eurostat (2018) about the share of workers in Portugal who report that they work from home at least occasionally, the proxy is consistent with this share if a firm policy of allowing remote work applies to or is taken up (at least occasionally) by 40-45 percent, on average, of the potential targets for such a policy, which does not seem unreasonable.

The information in SCIE is gathered from two detailed financial statements (balance sheet and income statement), which implies that we have a rich set of information about each firm. Key variables include gross output, value added, capital stock, employment, wage bill, industry affiliation and a firm death indicator.[9] In addition, the dataset includes workforce characteristics such as gender distribution and share of part-time workers, and information on whether the firm provides formal training or incurs social expenses for the benefit of the workforce. The data also include information about firms' involvement in research activities and about the share of each firm's sales that is exported. These and other variables used in the empirical analysis are described in Table A1 in the Appendix.

We match 8525 unique firms for which we have complete information on all variables during the period of analysis. Among these, we eliminate 6880 firms that appear only once during the panel and are thus not suited for estimations of models with firm-fixed effects. This leaves us with a panel of 1644 firms, among which 1149 (101) always (never) give their employees remote access in any year during the period of analysis. Among the remaining 394 firms, 230 do not give remote access in the first year they appear in the dataset, but do so in a later year, whereas 164 firms remove the possibility of remote access after giving it in the first year of observation.[10] These 394 'switchers' are key to our empirical identification strategy, which is based on the estimation of models with firm-fixed effects, thus relying on within-firm variation in remote access as the source of identification. In the Appendix we show how the firms in our final sample are distributed, according to whether or not they give workers remote access, across different industries (Table A2) and across different categories of firms (Table A3) that we use in our analysis of inter-firm heterogeneity in Section 6. These tables reveal that both types of 'switchers' are reasonably represented in most industries and in all firm categories considered.

Our final sample consists of 4726 firm-year observations, where more than half of the 1644 firms are observed in at least three years. In the Appendix, summary statistics for the main variables are displayed in Table A4, and equivalent summary statistics for subsamples constructed according to firm size are given in Tables A4.1-A4.3. Furthermore, the characteristics of the panel in terms of repeated observations are shown in Table A5. Given the sampling design of the IUTIC survey, it should be noted that our final sample is biased towards larger firms, since the sample includes the

[9] The dataset also includes a firm birth indicator which is not used as it is collinear with other regressors.

[10] From the initial sample of 8525 firms, we had already excluded 66 firms (253 observations) that change their policy on remote access more than once during the period of analysis.

population of large firms, whereas the remaining firms are randomly chosen within size categories in each industry.[11] In our empirical analysis we address this sampling issue in two different ways. First, we partially correct for the overrepresentation of large firms by applying sampling weights in one of our robustness checks in Section 5. Second, as one of several extensions to our benchmark analysis, we explore the possibility of heterogeneous effects across different firm sizes (in Section 6).

In Table 1 we report the mean values of the variables, averaged over all firm-year observations in which remote access was given, or not, by the firm. The last column presents the statistical difference (given by a t-test) of the means of these variables for the two categories of firm-year observations. The mean values reported in the first three rows might give some support to the view that firms often provide 'bundles' of complementary human resource management practices (e.g., Ichnioswski et al., 1997; Black and Lynch, 2004; Bloom et al., 2011). In our context, firms that give remote access also invest more in workers' firm-specific skills (proxied by training costs per worker) and have a higher level of social expenses per worker.

[Table 1]

The productivity differential between the two categories of firms is large and statistically significant, whether measured by sales per worker or value added per worker, suggesting that giving workers remote access might be associated with higher firm labour productivity. Additionally, Figure 1 shows that the productivity distribution of firms that give remote access lies to the right of the equivalent distribution of those that do not give remote access. This pattern is consistent with previous research on the positive association between telecommuting (and more generally, human resource management practices) and productivity (e.g., Konrad and Mangel, 2000; Bailey and Kurland, 2002; Bloom et al., 2015).

[Figure 1]

A similar differential is also observed in terms of input use. Firms that give remote access use much more capital and materials per worker, suggesting that these firms tend to be larger. This appears consistent with the view that large firms tend to adopt work-life practices to a larger

[11] Whereas the share of large firms in our final sample is 31 percent, the corresponding share in the entire population of Portuguese firms is less than 1 percent.

extent, possibly due to economies of scale and more vulnerability to internal pressures (Konrad and Mangel, 2000).

The two categories of firm-year observations also differ significantly in terms of ICT diffusion and also in terms of workforce characteristics. Firms that give remote access employ a relatively larger proportion of workers that use PC, and they also employ a higher share of workers involved in R&D activities. Furthermore, their workforce is on average more skilled, as proxied by the average wage paid by the firm.[12]

In terms of gender composition of the workforce, the values in Table 1 indicate that firms that give remote access also employ a higher proportion of men, which appears inconsistent with the view that firms employing a larger share of women also develop more human management practices aiming at reducing work-life conflicts, such as costs related to absenteeism. However, the empirical evidence on this link is mixed (e.g., Konrad and Mangel, 2000, and Bloom et al., 2011).

The values reported in Table 1 also indicate that remote access is positively associated with the firm's export to sales ratio, but negatively associated with the degree of product market competition. The latter association can perhaps be seen as being consistent with previous literature suggesting that additional external pressure on the firm leads to higher internal pressure, longer working hours, and ultimately leads to a reduction in the provision of human resource practices (Bloom et al., 2011).

Finally, in terms of industry affiliation, firms that give remote access are significantly more prevalent in service industries, though the difference in magnitude is quite small. This pattern is consistent with previously reported evidence from the US, which indicates that a wide range of human resource management practices prevail in the service industries (Konrad and Mangel, 2000).

4 Empirical strategy

Our empirical strategy follows the literature (e.g., Bloom et al., 2019), and is based on the estimation of an augmented Cobb-Douglas production function. As a starting point, consider the following

[12] In the absence of information about formal schooling or other more direct measures of worker skill, we use the average wage paid by a given firm as a proxy for the skill level (or skill intensity) of the firm's workforce. Though not a perfect measure, it is commonly used in the literature (e.g., Head and Ries, 2002; Autor and Dorn, 2013; Atasoy et al., 2016).

normalised (on labour) production function:

$$\ln\left(\frac{Y}{L}\right)_{it} = \alpha \ln\left(\frac{K}{L}\right)_{it} + \beta \ln\left(\frac{M}{L}\right)_{it} + \gamma \ln L_{it} + \theta R_{it} + \delta' Z_{it} + v_t + \varepsilon_{it}, \tag{1}$$

where Y_{it} is the real value of output measured by total revenues/sales, K_{it} is the real value of total tangible assets, M_{it} is real intermediate inputs, and L_{it} is the number of workers in firm i at time t.[13] Furthermore, R_{it} is an indicator variable that identifies if, at time t, firm i allows its workers to have remote electronic access, Z_{it} is a vector of variables to account for differences in several observable attributes of the firm, the vector v_t controls for time-specific shocks that are common to all firms, and ε_{it} is an error term.

The vector Z includes a wide set of variables to control for observable characteristics of the firm along several dimensions. First, we include a group of variables to account for the use of other management practices by the firm, namely training costs per worker, social expenses per worker, and the share of full-time workers. Second, we control for ICT diffusion by including the share of workers using a PC (at least once per week). Third, we control for other workforce characteristics by including the share of male workers, the share of workers involved in R&D activities, and the average level of worker skills (proxied by the average wage). Fourth, we account for differences in product market competition, measured by the Herfindahl-Hirschman Index, and export activities. Finally, in order to control for the event of firm exit from the market, we include an indicator variable that takes the value of one if the firm closed down during the year. Given the wide scope of our analysis, using data from a wide range of economic sectors, we convert all financial variables to real terms using deflators defined according to three different sectors: agriculture, manufacturing and services.[14]

A potential criticism of our empirical strategy concerns the timing of the impact of enabling (or disabling) remote access. Our specification assumes that the effect occurs immediately in the organisation. However, the implementation of human resource practices might be a somewhat longer-term process of culture building that involves changes in workers' behaviour over time (e.g., Huselid and Becker, 1996). One way to account for the nature of this process would be to include time-lagged variables in the model specification. We choose not to follow this approach for two

[13] Notice that, by including (log of) labour as an independent variable, we allow for the possibility of non-constant returns to scale (if the coefficient γ is significantly different from zero).

[14] We use 2016 deflators from AMECO, which is a macroeconomic database of the European Commission (https://ec.europa.eu/info/business-economy-euro/indicators-statistics/economic-databases/macro-economic-database-ameco/ameco-database_en).

reasons. First, the short length of our unbalanced panel data would imply a large loss of firms and observations. Second, and most importantly, the remote access variable is measured at a different point in calendar time than the other variables. According to the IUTIC survey, the remote access variable reflects the practice status in January of each year, whereas the output/input variables refer to the corresponding values at the end of each year. Thus, for each calendar year of observation, our data already contain a time lag of practically one year between the recorded measures of our main independent variable and the other main variables in the production function, and we believe that this goes a long way towards allowing for a potential sluggishness in the effect of enabling (or disabling) remote access.

Despite the fact that we are able to estimate the model on longitudinal data with a very rich set of controls, our estimates might be subject to at least two different sources of endogeneity. First, productivity differences between firms that enable and firms that do not enable remote access might be caused by some systematic differences between these two groups of firms along unobserved dimensions. We therefore exploit the panel structure of our data set and include firm-fixed effects to account for unobserved time-invariant heterogeneity across firms. This implies that the identification of the relationship between remote access and productivity is based on within-firm changes in remote access over time and not by permanent unobserved differences across firms. More specifically, the effect is identified by a difference-in-differences estimator where treated firms (i.e., firms that change their policy on remote access during the period of observation) are compared to untreated firms (i.e., firms that never or always enable remote access).

Second, our results may still be subject to omitted variable bias, such as demand shocks that affect both the choice of enabling remote access and firm labour productivity. Alternatively, some firms might simultaneously enable remote access and invest in other productivity-enhancing activities, leading to spurious correlations between these two variables. Some of these potentially confounding firm-level trends can be due to business cycles. Therefore, we also include industry-specific time trends in the estimated equation to allow for differential technological progress by industry and to control for industry-specific business cycle effects that lead to differential intensity in the use of production factors.

5 Results based on the full sample of firms

We present our empirical results in three stages. In this section we first show the results from estimating different versions of (1) using all firms in our sample. Then we test the robustness of the results derived from the most comprehensive (and our most preferred) specification of (1). These robustness checks include additional controls, alternative definitions of key variables, and alternative sample selection strategies. We then proceed in the next section by re-estimating our preferred model using several different partitions of the data, which allows us to uncover potentially heterogeneous relationships between remote access and labour productivity.

5.1 Remote access and firm labour productivity

Table 2 shows results from the estimation of (1), using all firms, when the dependent variable is log of sales per employee. The first two columns present the results from regressions without firm-fixed effects, where identification is to a large extent based on across-firm variation. In the first column, we report the estimates based on the simplest version of (1), where only time-fixed effects and industry trends are added to the basic Cobb-Douglas specification, whereas the second column shows estimation results with further controls included, such as variables capturing the effects of other human resource management practices (share of part-time workers, and training costs and social expenses per worker), differences in ICT diffusion, workforce composition, firm exit, export intensity and product market competition.

[Table 2]

Regarding our main variable of interest – whether or not employees are given remote electronic access – the estimates from the first column indicates a positive and statistically significant association between remote access and labour productivity. This evidence is consistent with earlier findings on the productivity effects of remote work reported in the literature, as discussed in Section 2, that are based on individual worker-level measures or firm-level data. However, as is evident from the estimates reported in column 2, the magnitude of the point estimate on the remote access variable drops dramatically, and ceases to be statistically significant, when we include the full set of control variables. Thus, when we rely mainly on cross-sectional variation to identify the association between remote access and productivity, our results are reasonably consistent with the ones reported by Bloom et al. (2011), who analyse the effect of an index measure of several human resource management practices in a cross-sectional sample of firms.

In the last two columns of Table 2, we report the estimation results from specifications of (1) where we exploit the panel structure of our data and account for time-invariant firm heterogeneity by including firm-fixed effects. Evidently, this makes a crucial difference. When identification is based on within-firm variation, the association between our two main variables is *reversed*, and we find a *significantly negative* association between remote access and firm labour productivity. Our estimates indicate that remote access is associated with a productivity loss of more than three percent. Notice also that both the magnitude and the precision of the estimate for our main coefficient are practically identical in columns 3 and 4, i.e., whether we include the full set of controls or not. Based on the Akaike information criterion, our preferred model is the specification which controls for the full set of worker and firm characteristics (i.e., column 4), so we will we base our subsequent analysis on this specification. However, it should be emphasised that all subsequent results are qualitatively identical and quantitatively very similar if we instead use the more parsimonious version of the model without the full set of controls (corresponding to column 3 in Table 2).

Once we control for time-invariant firm heterogeneity, the remaining key firm/worker characteristics determining firm labour productivity are average wage, export share and firm exit. As expected, the estimated coefficients are positive for the first two variables and negative for the third. Perhaps surprisingly, there is no significant productivity effect of the share of R&D workers, even in the specification without firm-fixed effects (column 2). This could potentially be a result of the constraints imposed by the underlying assumption that all firms have the same technology.[15] Finally, the significantly negative estimate of the coefficient on the variable $\ln L_{it}$ suggests that the 'average technology' is characterised by decreasing returns to scale.

5.2 Robustness checks

In the following we test the robustness of the results from our most preferred model, given by the estimates reported in column 4 of Table 2. The robustness checks are performed along four different dimensions, regarding (i) key variable definitions and sample selection, (ii) additional controls, (iii)

[15] Indeed, our analysis in Section 6 show that the relationship between the share of R&D workers and firm labour productivity is significantly positive, even when including firm-fixed effects, if we restrict the sample to all firms that undertake some R&D activities. A similar effect is found for medium-sized firms.

alternative outcome measures, and (iv) firm selection.

5.2.1 Remote access intensity, sampling weights and measurement error

In our benchmark analysis we measure remote access as an indicator variable, implying that each firm is classified as either enabling remote access or not. However, enabling remote access might have different effects across different firms depending on the share of the workforce that is potentially affected by such a policy. As previously mentioned, we are not able to observe this share directly. However, our data do include information that allows us to determine an upper bound on this share, namely the share of workers that use a computer in their work. By interacting this share with the remote access indicator, we obtain a continuous measure that potentially captures remote access *intensity*, i.e., the extent to which remote access enablement potentially affects the firm's workforce.[16]

Furthermore, and as mentioned earlier, our sample is biased towards large firms, since all large firms, but only a sample of small and medium-sized firms, are included in the IUTIC survey. We can test for the potential importance of this bias by re-estimating (1) using the sampling weights (computed in terms of total revenues) provided by the survey.[17]

Finally, we want to check if and how our main result might be affected by potential measurement error in the remote access variable. Our full sample consists of 164 firms that abandon a remote access policy that was previously in place. *A priori*, and given the increasing trend of remote work, the disabling of remote access might appear harder to explain than remote access enablement. One possible explanation is of course provided by our main result reported above, namely that remote access is negatively associated with firm labour productivity, on average. However, given that there are likely other considerations at play when firms make this type of decision, we cannot rule out the possibility that some of the observations result from measurement error. If such errors exist, we hypothesise that the observation of remote access disablement is more likely to be a result of measurement error in cases where firms are observed to abandon the policy in the last year of the observation period, since in these cases there are no confirming observations in subsequent years.

[16] In order to be able to interpret this variable as measuring remote access intensity, we need to exclude the share of PC workers as an independent variable in the regression. Notice, however, that this variable is statistically insignificant in our preferred empirical model.

[17] Notice that, although the sampling weights correct for the overrepresentation of large firms in a single draw from the population, they cannot fully correct for this in a panel consisting of yearly independent draws, since, for the smaller firms, the probability of being drawn in more than one year is less than the probability of being drawn in a single year.

Thus, as a robustness check for potential measurement error, we re-estimate (1) on a sample where we remove the firms that are observed to disable remote access in 2016, which actually constitutes a large share of the observed remote access ‘disablers’.[18]

[Table 3]

The results from these three robustness checks are presented in Table 3, where the estimates given in the first column correspond to those of the last column in Table 2, and where we show results for both remote access measures (discrete and continuous) also in the two other robustness checks. Comparing the results in columns 1 and 2, we see that the use of a continuous remote access variable has practically no effect on the magnitude of the point estimate of the main coefficient of interest, but the coefficient is less precisely estimated.

The use of sampling weights, on the other hand, has the opposite effect, causing the main coefficient estimate to increase both in magnitude and in precision. In the weighted sample, the association between remote access and labour productivity is statistically significant also when using the continuous remote access measure. This suggests that the effect of remote access is heterogeneous across different-sized firms, something that will be further explored in the next section.

Finally, the estimation results displayed for the restricted sample in column 5 suggest that our main result based on the full sample is unlikely to be explained by measurement error in the remote access variable. The association between remote access and labour productivity is still significantly negative and even slightly larger in magnitude when we exclude observations that are more likely to be prone to measurement error.

With the caveat that measurement error might be an issue for firms that are observed to abandon a policy of enabling remote access, we have also investigated whether the relationship between remote access and labour productivity is different for firms that switch from enabling to disabling remote access than for firms that switch in the opposite direction. However, we do not find a statistically significant indication of such asymmetric effects.[19]

[18] More precisely, we remove all observations of firms for which the remote access variable takes the value 0 in 2016 and 1 in all previous years in which the firm is observed. These firms constitute 147 of the 164 observed cases of firms disabling remote access.

[19] Details of this analysis are available upon request.

5.2.2 Managerial effects

In our preferred model, with firm-fixed effects, identification of a statistical association between remote access and firm labour productivity is based on within-firm variation in the former variable; in other words, the association is identified by firms that either enable or disable remote access during the period of analysis. However, it might be the case that a change in remote access practice coincides with other changes at the firm that could have an impact on productivity, thereby confounding the estimated association between remote access enablement and productivity. More specifically, a change in remote access practice might be instigated by a managerial change in the firm, which in itself might have a direct impact on labour productivity. Although we cannot observe managerial changes directly, we use information about the overall CEO compensation of the firm available in the dataset to account for the size and quality of managers. We compute two alternative measures (both in logs), namely (i) CEO compensation per worker and (ii) share of sales revenues spent on CEO compensation. The underlying assumption is that managerial changes are likely to be reflected by changes in at least one of these measures.

[Table 4]

If we account for potential managerial effects by including either of the two above described variables as additional controls, we obtain the results reported in Table 4. The first column contains the estimate that correspond to the previously reported estimate from our benchmark model.[20] If we control for managerial quality, we see that the remote access coefficient remains very similar both in magnitude and statistical significance, which is reassuring for the robustness of the results.

5.2.3 Alternative outcome variables

As a final robustness check, we examine whether remote access has a similar effect on two alternative (but related) outcome variables: (i) log of value added per worker, which is an alternative measure of firm labour productivity, and (ii) operational profits, which is a broader measure of firm performance. Both these measures are given directly by the SCIE data.

[Table 5]

[20] This estimate is somewhat larger in magnitude compared to the estimate in the last column of Table 2. This difference can be attributed to the difference in sample size caused by missing data on managerial compensation.

We re-estimate the most comprehensive version of (1) using these alternative outcome measures. The resulting estimates are reported in Table 5. Although all the point estimates are negative, they are much less precisely estimated than in the benchmark regression, particularly when using operational profits as the outcome variable. Although value added per worker is conceptually much closer (than profits) to our main outcome measure, the main difference lies in the fact that a productivity measure based on value added is less sensitive to substitution between labour and other inputs. Thus, the fact that we obtain a statistically insignificant association between remote access and value added per worker might suggest that the significantly negative association between remote access and sales per worker is partly caused by efficiency losses that are related to factor substitution.

In sum, we conclude that, regardless of which outcome measure we use, we are not able to detect a positive relationship between remote access and firm productivity (or performance) using the full sample, and the relationship is significantly negative when considering firm labour productivity as measured by sales per worker.

5.2.4 Firm selection

Whether or not a firm allows its workers to have remote electronic access is not likely to be exogenous. A potential worry might therefore be that our results are subject to firm selection bias. We explore this issue by using a propensity score matching approach, where we match firms that switch to allowing remote access with firms that never allow remote access, and firms that remove remote access with firms that always allow remote access. We estimate the propensity score using lagged (and logged) values of sales, sales per worker, capital, intermediate inputs, and average wage as explanatory variables, in addition to industry-, region- and firm-fixed effects. We perform exact matching according to year, industry, region and firm size category. Within these cells, we use one-to-one nearest neighbour matching without replacement, imposing a bandwidth of 0.05.[21] Our approach implies that each 'switching' firm is matched with a firm with similar productivity (within the same industry, region and size category) in the year before the change in remote access policy.

The main drawback with this approach is that we lose a lot of firms/observations in the matching procedure, thus leaving us with a fairly small sample of firms in the end. Our results should

[21] Further details on the matching procedure and on the quality of matching are available upon request.

therefore be interpreted with some caution. Because of the potential concerns related to the subset of firms that abandon a remote access policy during our period of analysis, as previously discussed in this section, we re-estimate (1) on two different matched samples: one consisting of both types of 'switchers' and their mathced counterparts, and one consisting of only firms that adopt a remote work policy and their matched counterparts (which are firms that never allow remote access).

[Table 6 here]

The estimation results using the matched samples are displayed in Table 6. We see that, for both samples, the sign of the main coefficient estimate is negative and thus the same as in the benchmark analysis. However, the estimate is not statistically significant when using the full sample of matched firms. Interestingly, when using the sample based on matched 'adopters', the main coefficient estimate is not only significant but also considerably larger in magnitude than the equivalent estimate in the main benchmark analysis. Although these results must be interpreted with some caution due to small sample sizes, they nevertheless give us some confidence that our benchmark results are not overly driven by firm selection.

6 Inter-firm heterogeneity

Our results based on the full sample of firms might mask considerable heterogeneity across firms and industries. The theoretical literature suggests that delegating more authority to workers, for example in the form of home-working entitlements, involves a basic trade-off. On the one hand, it might increase worker effort through increased intrinsic motivation (e.g., Ellingsen and Johannesson, 2008) or through reciprocity (e.g., Dur et al., 2010). On the other hand, it makes monitoring more costly and therefore leads to a loss of control for the employer. This might have a negative effect on worker effort, either directly through increased 'shirking' or indirectly through a reduction in extrinsic incentives caused by increased monitoring costs (Beckmann et al., 2017).

The balance of the above described trade-off is likely to differ according to the type of jobs involved and the nature of the employer-worker relationship, and it is thus likely to depend on a number of firm-specific and industry-specific factors. One potentially important distinction is explored by Dutcher (2012), who reports experimental evidence suggesting that remote work can lead to opposite effects on productivity depending on the level of *creativeness* required by the workers. More specifically, out-of-office work can lead to a decline in productivity for routine, manual and repetitive tasks, whereas the opposite is true for cognitive and creative tasks. In light of this, the effect on firm labour productivity of enabling remote work is likely to depend on the relative shares of creative and routine jobs, which in turn is likely to vary considerably across firms and industries.

In this section we explore the potential existence of such heterogeneous effects across different types of firms. We do this by making several partitions of the data and estimate the most comprehensive version of (1) on different subsamples. Although comparison of coefficient estimates across different regressions is more challenging, the use of subsample regressions is motivated by the concern that estimating a single production function for very different types of firms might be overly restrictive. Indeed, for all of our partitions, F-tests show that the assumption of equal coefficients across different subsamples does not hold, thus justifying the approach of estimating separate production functions.

6.1 Worker and job characteristics: R&D activities and skill level

We start out by partitioning the data according to what we hypothesise to be a key factor in determining any heterogeneous effects of enabling remote access, namely the above described distinction between creative and routine tasks. Since this is not directly observable in the data, we construct two different variables that we believe capture this distinction to some extent, at least. First, we create an indicator variable that distinguishes between firms that undertake R&D activities and firms that do not. All else equal, it seems reasonable to assume that the prevalence of 'creative tasks' will be higher in the former category of firms.

A similar effect might also be captured by considering the skill-level of the firm's workforce, if there is a positive relationship between the share of high-skilled workers and the share of creative tasks, which seems a plausible assumption. Therefore, we also split the sample according to the average skill-level of the firm's workforce, proxied by the average wage level in the firm relative to that of the corresponding industry.[22] More precisely, within each industry, the firms with an average wage level above the mean of the industry are classified as *high-skill* firms, whereas the remaining firms are classified as *low-skill* firms.

In Table 7 we report the results from a re-estimation of (1) when we distinguish between low-

[22] Using Portuguese data for the period 1998 to 2013, Portugal et al. (2018) estimate that almost 80 percent of wage changes can be attributed to changes in workers' qualifications. Based on this, we expect the average wage paid by a firm to be a reasonable proxy for the (average) skill level of its worforce.

skill and high-skill firms (columns 1 and 2), and between firms without and with R&D activities (columns 3 and 4). As a first observation, the differences in production technology appear more noticeable between firms with and without R&D activities. For example, the estimated coefficient on the variable $\ln L_{it}$ suggests that firms without R&D activities are (on average) characterised by decreasing returns to scale, whereas this is not the case for firms that undertake R&D.

[Table 7]

Regarding our main variable of interest, the results indicate that both partitions displayed in Table 7 are relevant in explaining potentially heterogeneous effects of remote access. Furthermore, the results are to a large extent consistent with our theoretical hypothesis. Regarding skill level, we find a significantly negative association between remote access and labour productivity in the subsample of low-skill firms. For the high-skill firms, on the other hand, the point estimate is positive though not statistically significant. Besides indicating an effect related to creative versus routine tasks, these results can perhaps also be seen as a partial confirmation of a hypothesis put forward by Bloom et al. (2011), who suggest that family-friendly workplace practices might have a positive productivity effect only for a subset of high-skilled workers.

The results for the subsample regressions related to R&D activities are even stronger and more clear-cut. In the subset of firms that do not undertake R&D, which is the large majority of firms, the association between remote access and labour productivity is significantly negative. However, for the other type of firms, in which some R&D activities are performed, the same association is significantly *positive*. Taken together, we believe that the results in Table 7 give relatively strong support to the hypothesis that enabling remote access has differential effects on productivity depending on the nature of the jobs involved, where such a policy is less likely to yield positive productivity gains in firms characterised by a large share of low-skilled and non-creative (routine) tasks.

6.2 Firm and industry characteristics: Size, industry type and export status

We now proceed to make three other potentially relevant partitions related to firm and industry characteristics. Our first partition splits the sample according to firm size. We define firms as being *small* if they have less than 50 workers, *medium-sized* if they have at least 50 but less than

250 workers, and *large* if they employ at least 250 workers.[23] Second, we allocate firms into two broad categories of industry affiliation, namely manufacturing and services. Finally, we classify firms according to whether or not they are engaged in export activities.

Each of these partitions are potentially relevant with respect to the basic trade-off involved in the firm's decision of whether or not to enable its employees to work remotely, as previously discussed. For example, it is well documented that exporting firms tend to be more productive and also more innovative than firms that do not export (see, e.g., Cassiman et al., 2010, and further references therein). Thus, export status might work as an alternative proxy for a firm's share of high-skilled or creative jobs. Firm size, on the other hand, might affect the aforementioned trade-off through the cost of control. It seems reasonable to assume that monitoring of workers (who do not work remotely) is easier in smaller firms than in larger firms, all else equal. Thus, it might be the case that enabling remote work implies a larger loss of control in smaller firms and thereby reduces the scope for a beneficial effect of such a policy.

The results from a re-estimation of (1) on each of the subsamples related to firm size, export status and industry affiliation are displayed in Table 8. Once more, there appears to be significant differences in production technology for firms belonging to different subsamples. As we would intuitively expect, our estimates suggest that small firms are characterised by decreasing returns to scale, whereas medium and large firms are characterised by constant returns to scale, on average. More surprisingly, decreasing returns to scale also appears to be more prevalent for exporting firms. This could however be explained by a large heterogeneity of firms within the subsample of exporters, ranging from firms with an infinitesimal export share to firms that are exclusively exporters.

[Table 8]

Turning now to our main variable of interest, the results reveal significant differences across the partitions displayed in Table 8. Our most clear-cut results are related to firm size and export status, where we find a strong and highly significant negative association between remote access and labour productivity for small firms and for firms that do not export. For firms in the other categories, we find no statistically significant relationship between the two variables. Regarding industry affiliation, the point estimate of our coefficient of interest is more equal in sign and magnitude across the two subsamples (columns 4 and 5 in Table 8), but is statistically significant

[23] The classification of firms into small, medium and large is made according to the first observation of each firm during the period of observation, which implies that the classification of each firm is constant over time.

only for manufacturing firms, which might be explained by the lower number of observations in the subsample regressions.

In sum, our results in Tables 7 and 8 indicate that the relationship between remote access and labour productivity depends crucially on both job/worker characteristics and on firm characteristics. In order to make some further assessments about the relative importance of these different dimensions, we decompose our previously derived results in Table 7 according to firm size (small, medium and large). The results of this decomposition, presented in Table 9, allow us to assess the importance of firm skill type (columns 1 and 2) and R&D activities (columns 3 and 4) for a given category of firm size, and *vice versa*.

[Table 9]

The picture emanating from the results in Table 9 is quite illuminating. In columns 1 and 2 we see that firm size makes a significant difference to the association between remote access and labour productivity only for low-skill firms, which might suggest that skill level is more important than firm size. This conclusion appears to be even clearer if we categorise firms according to whether or not they perform R&D. The results in columns 3 and 4 show that the negative association between remote access and productivity only applies for the subset of small firms that do not perform R&D. For the rest of the small firms, the corresponding association is significantly *positive*. Among the firms that undertake R&D activities, we also detect a significantly positive association for medium-sized firms, which suggests that firm size is not particularly relevant in explaining the relationship between remote access and labour productivity for this subset of firms.

Overall, we believe that the results shown in Table 9 give some indications that worker and job characteristics are more important than firm size in explaining the heterogeneity of our results, and that the effects of firm size are partly explained by an unequal firm size distribution across other, and more important, firm characteristics. For example, the descriptive statistics show that the share of firms that do not undertake R&D activities is much higher among small firms than among medium-sized and large firms.[24] In the same vein, the importance of export status, as shown in columns 6 and 7 of Table 8, might to some extent be explained by the fact that the share of firms performing R&D activities is much larger for exporters than for non-exporters (22 and 4 percent, respectively).

[24] The share of small firms performing R&D is less than 5 percent. For the full sample of firms, the corresponding share is almost 20 percent.

As the above discussion indicates, there is a considerable degree of subsample overlap across the different firm characteristics that are conducive to a significantly negative association between remote access and labour productivity, in the sense that many firms that do not export, for example, are also small firms that do not perform R&D activities and employ a workforce with a below-average skill level. In our sample, we can identify 248 firms that have all these four characteristics, and 105 of these firms changed their practice on remote access during the period of observation. If we estimate our preferred empirical model on this particular subsample of firms, we find a very strong and highly significant negative association between remote access and firm labour productivity. In these firms, allowing for the possibility of remote access is associated with a productivity loss of more than 19 percent.[25] The magnitude of this association, which is considerably larger than the corresponding estimates for any other subsample previously reported, give further indication that the negative average association between remote access and firm labour productivity is strongly driven by a subsample of firms with a particular set of characteristics.

7 Concluding remarks

Although previous empirical evidence indicates positive productivity effects associated with the possibility of working remotely, experimental evidence points to mixed effects, which is more in line with existing theory. In this paper we have contributed to the literature on remote work and productivity by empirically analysing the effect of remote electronic access on firm labour productivity, with the underlying assumption that remote access is a proxy for remote work enablement. Our analysis is conducted using a longitudinal panel dataset of firms in a sample that is representative of the Portuguese economy, including manufacturing and services industries, and where the existence of within-firm variation in remote access allows us to estimate models with firm-fixed effects, where identification relies on firms that, during the period of observation, either adopt or abandon a policy of allowing remote access to its workers.

Our main contribution is the uncovering of heterogeneous productivity effects across different types of firms and industries. Although we find that remote access is associated with a statistically significant loss in firm labour productivity of around 3.3 percent when using the full sample of firms, we also show that this overall negative effect masks a substantial degree of heterogeneity across different sub-samples of firms. More specifically, the negative average association is mainly driven

[25] The full set of regression results is available upon request.

by small, non-exporting firms which do not undertake any R&D activities and employ a workforce with a below-average skill level. In particular, our detailed analyses suggest that the presence (or not) of R&D activities is a key distinction between firms. In fact, for the subset of firms that undertake R&D, we find that remote access is significantly and *positively* associated with labour productivity. This suggests that the productivity effects of remote work enablement might crucially rely on job characteristics, and we interpret our results as providing a tentative confirmation of previous experimental evidence presented by Dutcher (2012), showing that remote work positively (negatively) affects productivity for creative (routine) tasks.

Our analysis is obviously not without weaknesses. One important drawback is the lack of information about which type of formal remote work arrangements (if any) that are in place for firms that allow its workers remote electronic access to e-mail, documents and applications. Obviously, we also do not know the share of workers who take up the option of working remotely in firms where this is allowed. Another drawback is the relatively short length of the panel, although we are able to identify a reasonably large number of firms (almost 400) that change their policy on remote work, in one or the other direction, during the period of observation.

Despite these weaknesses, we do believe that our study makes important contributions, both to the academic literature and to corporate decision makers. In a context where digital technologies allow a seamless adoption of remote work within firms, policy makers are increasingly calling for more flexible work arrangements to allow workers to better manage the work-life balance (European Commission, 2017). However, many firms might be reluctant to introduce or extend such practices, since 'hard-nosed evidence to support the business case for family-friendly policies is not overwhelming' (OECD, 2007, p. 187). In this respect, our paper fills a gap in terms of empirical evidence on the effect of remote work on firm labour productivity. In particular, we believe that our analysis provides potentially important insights about which firm characteristics are conducive to a positive or negative productivity effect of allowing employees to work remotely.

Appendix: Variables and summary statistics

Table A1 contains definitions and descriptions of the variables used in the analysis.

[Table A1]

In Table A2 we show the distribution of firms according to remote access status in each of 20 industries. Similar distributions for sub-categories of firms classified according to firm size, R&D activities, skill level and export status are displayed in Table A3.

[Table A2]

[Table A3]

Table A4 contains summary statistics of our main variables for the full sample of firms. Equivalent statistics for small, medium-sized and large firms are provided in Table A4.1, Table A4.2 and Table A4.3, respectively.

[Table A4]

[Table A4.1]

[Table A4.2]

[Table A4.3]

Table A5 shows the distribution of firm-year observations across the 1644 firms in our final sample.

[Table A5]

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Figure 1: Distribution of firm labour productivity across firms

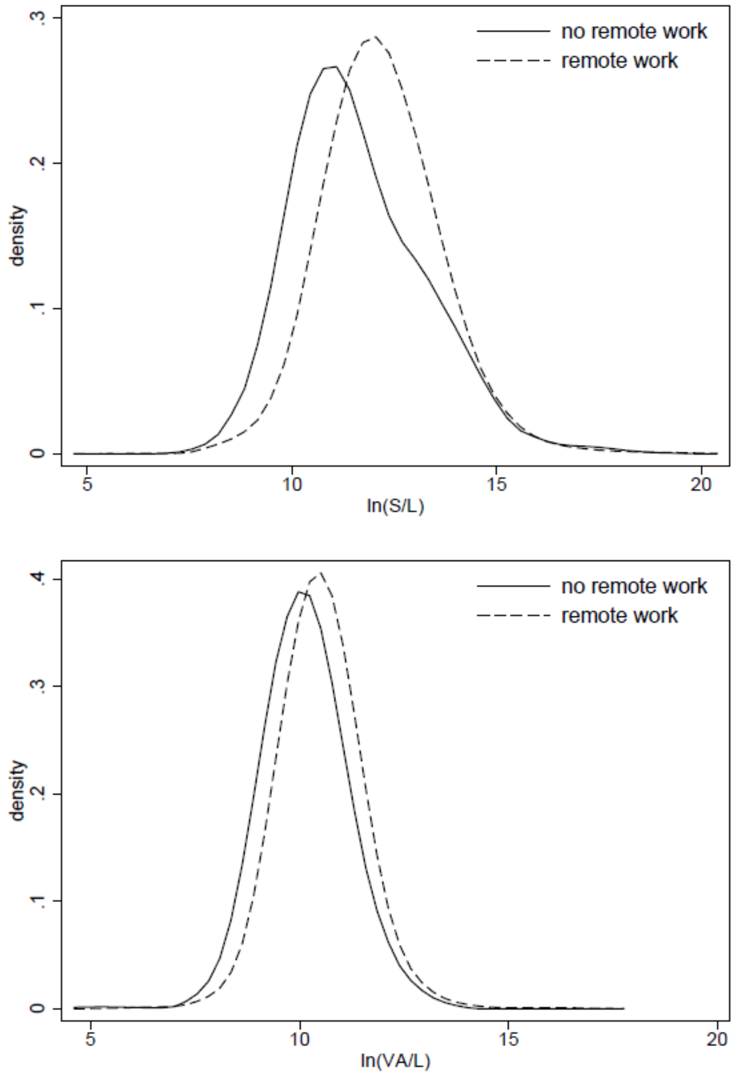

Table 1: Mean values for firms that give and do not give remote access

VARIABLES	Remote access	No remote access	Difference	
Part-time (%)	0.0320	0.0292	0.0028	
Training costs per worker	0.0093	0.0034	0.0059	***
Social expenses per worker	0.0336	0.0098	0.0238	***
ln(Y/L)	12.1826	11.632	0.5506	***
ln(VA/L)	10.5009	10.1282	0.3727	***
ln(K/L)	10.0229	9.3878	0.6351	***
ln(M/L)	11.2022	10.5567	0.6455	***
PC (%)	0.5075	0.3937	0.1138	***
ln(wage)	9.7444	9.4425	0.3019	***
Males(%)	0.6508	0.6133	0.0375	**
R&D workers (%)	0.0108	0.0053	0.0055	**
Exit	0.0029	0.0016	0.0013	
Services	0.5363	0.4867	0.0496	*
Export to sales ratio	0.2654	0.1751	0.0903	***
HHI	0.1027	0.0773	0.0254	***
# observations	4089	637	4726	
# firms	1543	495	1644	

Notes: ***, ** and * indicate that the difference in means is statistically significant at the 1%, 5% and 10% level, respectively. The standard errors are clustered at firm level.

Table 2: Remote access and labour productivity

VARIABLES	(1) ln(Y/L)	(2) ln(Y/L)	(3) ln(Y/L)	(4) ln(Y/L)
Remote access	0.1440***	0.0303	-0.0325*	-0.0336*
	(0.0365)	(0.0307)	(0.0183)	(0.0176)
ln(K/L)	0.0446***	0.0173*	0.0209	0.0146
	(0.0122)	(0.0103)	(0.0184)	(0.0188)
ln(M/L)	0.5502***	0.4723***	0.3942***	0.3706***
	(0.0188)	(0.0179)	(0.0390)	(0.0386)
ln(L)	-0.0340***	-0.0677***	-0.2133***	-0.1969***
	(0.0118)	(0.0110)	(0.0513)	(0.0544)
Part-time (%)		0.3704***		0.0101
		(0.1117)		(0.0855)
Training costs per worker		0.6485**		0.3892
		(0.3242)		(0.3734)
Social expenses per worker		-0.1857		0.2217*
		(0.1510)		(0.1310)
PC (%)		-0.0014		0.0195
		(0.0471)		(0.0456)
ln(wage)		0.7596***		0.2657***
		(0.0428)		(0.0783)
Males(%)		-0.1494**		0.1299
		(0.0610)		(0.1015)
R&D workers (%)		-0.2957		-0.0597
		(0.2098)		(0.4012)
Exit		-0.3704***		-0.2475***
		(0.1006)		(0.0819)
Export to sales ratio		0.0967**		0.1418**
		(0.0458)		(0.0647)
HHI		0.5769***		0.0562
		(0.1027)		(0.2016)
Year FE	Yes	Yes	Yes	Yes
Industry trends	Yes	Yes	Yes	Yes
Firm FE	No	No	Yes	Yes
# observations	4726	4726	4726	4726
# firms	1644	1644	1644	1644
Adjusted R^2	0.826	0.870	0.461	0.486
Residual sum of squares	1604	1194	130.6	124.2

Notes: Significance level at which the null hypotheses is rejected: ***, 1%; **, 5% and *, 10%. The standard errors are clustered at firm level.

Table 3: Remote access and productivity: remote access intensity, sampling weights and measurement error

Sample	Unweighted		Weighted		Restricted unweighted	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	ln(Y/L)	ln(Y/L)	ln(Y/L)	ln(Y/L)	ln(Y/L)	ln(Y/L)
Remote access	-0.0336*		-0.0680**		-0.0392*	
	(0.0176)		(0.0269)		(0.0214)	
Remote access (continuous)		-0.0331		-0.1123***		-0.0119
		(0.0260)		(0.0424)		(0.0274)
ln(K/L)	0.0146	0.0147	-0.0122	-0.0123	0.0174	0.0173
	(0.0188)	(0.0189)	(0.0181)	(0.0178)	(0.0211)	(0.0213)
ln(M/L)	0.3706***	0.3703***	0.4509***	0.4520***	0.3792***	0.3789***
	(0.0386)	(0.0386)	(0.0530)	(0.0528)	(0.0391)	(0.0392)
ln(L)	-0.1969***	-0.2037***	-0.0969	-0.1013	-0.1841***	-0.1937***
	(0.0544)	(0.0535)	(0.0728)	(0.0703)	(0.0571)	(0.0565)
Other controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Industry trends	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
# observations	4726	4726	4726	4726	4341	4341
# firms	1644	1644	1644	1644	1497	1497
Adjusted R^2	0.486	0.486	0.574	0.574	0.491	0.490
Residual sum of squares	124.2	124.3	121.6	121.6	114.2	114.5

Notes: Significance level at which the null hypotheses is rejected: ***, 1%; **, 5% and *, 10%. The standard errors are clustered at firm level.

Table 4: Remote access and productivity: Controlling for managerial quality

VARIABLES	(1) ln(Y/L)	(2) ln(Y/L)	(3) ln(Y/L)
Remote access	-0.0505**	-0.0504**	-0.0459**
	(0.0240)	(0.0240)	(0.0203)
ln CEO compensation per worker		0.0040	
		(0.0135)	
ln CEO compensation to sales ratio			-0.1564***
			(0.0265)
ln(K/L)	0.0044	0.0044	0.0036
	(0.0255)	(0.0255)	(0.0221)
ln(M/L)	0.3744***	0.3743***	0.3215***
	(0.0504)	(0.0504)	(0.0449)
ln(L)	-0.1195	-0.1170	-0.2025***
	(0.0797)	(0.0791)	(0.0733)
Other controls	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Industry trends	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
# observations	3124	3124	3124
# firms	1204	1204	1204
Adjusted R^2	0.466	0.466	0.548
Residual sum of squares	72.74	72.73	61.60

Notes: Significance level at which the null hypotheses is rejected: ***, 1%; **, 5% and *, 10%. The standard errors are clustered at firm level.

Table 5: Remote access and alternative outcome measures

VARIABLES	(1) ln(VA/L)	(2) Operational profits
Remote access	-0.0066	-0.0870
	(0.0217)	(0.3879)
ln(K/L)	0.0260	
	(0.0211)	
ln(L)	-0.1551**	0.9050
	(0.0756)	(0.8105)
ln(K)		0.3645
		(0.2492)
ln(M)		0.7135***
		(0.2727)
Other controls	Yes	Yes
Year FE	Yes	Yes
Industry trends	Yes	Yes
Firm FE	Yes	Yes
# observations	4652	4652
# firms	1637	1637
Adjusted R^2	0.108	0.00852
Residual sum of squares	300	208745

Notes: Significance level at which the null hypotheses is rejected: ***, 1%; **, 5% and *, 10%. The standard errors are clustered at firm level.

Table 6: Remote access and labour productivity - matched samples

		(1)	(2)
	Samples	Full	Only adopters
VARIABLES		ln(Y/L)	ln(Y/L)
Remote access		-0.0438	-0.1880**
		(0.0474)	(0.0893)
ln(K/L)		0.0452	0.1283*
		(0.0321)	(0.0667)
ln(M/K)		0.4809***	0.9212***
		(0.1047)	(0.2167)
ln(L)		0.0024	0.5500**
		(0.1019)	(0.2388)
Other controls		Yes	Yes
Year FE		Yes	Yes
Industry trends		Yes	Yes
Firm FE		Yes	Yes
# observations		601	148
# firms		210	55
Adjusted R^2		0.617	0.792
Residual sum of squares		12.23	2.50

Notes: Significance level at which the null hypotheses is rejected: ***, 1%; **, 5% and *, 10%. The standard errors are clustered at firm level. The full matched sample (1) includes 35 adopters, 83 abandoners and 92 control firms. The sample of matched adopters (2) includes 35 adopters and 20 control firms.

Table 7: Remote access and productivity: Skill level and R&D activities

	(1)	(2)	(3)	(4)
Samples	Low skill	High skill	No R&D	Yes R&D
VARIABLES	ln(Y/L)	ln(Y/L)	ln(Y/L)	ln(Y/L)
Remote access	-0.0528**	0.0231	-0.0408**	0.0390**
	(0.0245)	(0.0211)	(0.0194)	(0.0194)
ln(K/L)	0.0161	0.0194	0.0079	0.0326
	(0.0189)	(0.0446)	(0.0200)	(0.0215)
ln(M/L)	0.3725***	0.3551***	0.3689***	0.5372***
	(0.0559)	(0.0645)	(0.0406)	(0.0866)
ln(L)	-0.1325***	-0.2089*	-0.1890***	0.0358
	(0.0513)	(0.1215)	(0.0417)	(0.0443)
Part-time (%)	0.0314	0.1261	0.0265	-0.7012
	(0.1024)	(0.0996)	(0.0828)	(0.6572)
Training costs per worker	0.1977	0.7990***	0.5826*	0.1904
	(0.3716)	(0.2878)	(0.3230)	(0.2442)
Social expenses per worker	0.5354*	-0.0111	0.1930	0.3116
	(0.3003)	(0.0854)	(0.1424)	(0.3092)
PC (%)	0.0180	-0.0424	0.0024	0.0085
	(0.0583)	(0.0603)	(0.0493)	(0.0519)
ln(wage)	0.3301***	0.3086***	0.3195***	0.3351***
	(0.1097)	(0.0975)	(0.0651)	(0.0878)
Males(%)	0.1815*	-0.0342	0.0628	-0.1846**
	(0.1073)	(0.1988)	(0.0947)	(0.0912)
R&D workers (%)	0.3720	-0.3299		0.5520*
	(0.2576)	(0.2628)		(0.2932)
Exit	-0.2135***	-0.1193	-0.2371***	
	(0.0744)	(0.1111)	(0.0789)	
Export to sales ratio	0.1645*	0.1174	0.1485**	0.0284
	(0.0840)	(0.1426)	(0.0727)	(0.0715)
HHI	0.0826	0.7890*	0.0016	0.7037**
	(0.2859)	(0.4694)	(0.2529)	(0.2821)
Year FE	Yes	Yes	Yes	Yes
Industry trends	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
# observations	3223	1503	3981	745
# firms	1478	746	1487	308
Adjusted R^2	0.490	0.465	0.511	0.717
Residual sum of squares	70.87	17.25	109.20	2.464

Notes: Significance level at which the null hypotheses is rejected: ***, 1%; **, 5% and *, 10%. The standard errors are clustered at firm level.

Table 8: Remote access and productivity: Firm size, industry type and export status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Samples	Small	Medium	Large	Manufacturing	Services	Exporters	Non-exporters
VARIABLES	ln(Y/L)	ln(Y/L)	ln(Y/L)	ln(Y/L)	ln(Y/L)	ln(Y/L)	ln(Y/L)
Remote access	-0.0871***	0.0092	-0.0256	-0.0207	-0.0509*	0.0125	-0.1240***
	(0.0274)	(0.0382)	(0.0183)	(0.0187)	(0.0294)	(0.0132)	(0.0438)
ln(K/L)	-0.0023	0.0450	0.0322	0.0361***	-0.0133	0.0179	0.0088
	(0.0245)	(0.0295)	(0.0208)	(0.0127)	(0.0249)	(0.0201)	(0.0343)
ln(M/L)	0.4139***	0.4809***	0.2271***	0.4405***	0.3219***	0.4394***	0.2752***
	(0.0730)	(0.0497)	(0.0481)	(0.0623)	(0.0468)	(0.0427)	(0.0542)
ln(L)	-0.3710***	-0.0973	-0.0132	-0.3200***	-0.1160**	-0.2340***	-0.0440
	(0.1060)	(0.0619)	(0.0482)	(0.0839)	(0.0559)	(0.0724)	(0.0787)
Part-time (%)	-0.1300	0.1217	-0.0205	0.0805	-0.0692	0.1587	-0.0662
	(0.3609)	(0.1459)	(0.0388)	(0.2493)	(0.0606)	(0.1546)	(0.0940)
Training costs	0.3866	0.3713	-0.0255	-0.5558	0.6684*	-0.3058	1.2897***
per worker	(0.4742)	(0.3087)	(0.2845)	(0.5960)	(0.3804)	(0.3964)	(0.3054)
Social expenses	0.0766	0.0819	0.3451*	0.2158**	0.1922	0.3726**	-0.6899***
per worker	(0.1943)	(0.2439)	(0.1938)	(0.1056)	(0.1698)	(0.1445)	(0.1983)
PC (%)	0.0088	-0.0127	0.0973*	-0.0351	0.0264	0.0539	-0.0690
	(0.1123)	(0.0410)	(0.0521)	(0.0621)	(0.0548)	(0.0504)	(0.0751)
ln(wage)	0.0922	0.4145***	0.6187***	0.0893	0.4425***	0.0997	0.5178***
	(0.0871)	(0.0704)	(0.1003)	(0.1054)	(0.0993)	(0.1189)	(0.0764)
Males(%)	0.0691	0.1286	-0.1343	0.1372	0.0604	0.1852	-0.3553*
	(0.1387)	(0.1413)	(0.0866)	(0.1038)	(0.1487)	(0.1171)	(0.2124)
R&D workers (%)	-0.5155	0.7430**	0.1635	-0.2354	0.2123	0.0270	-0.4895
	(0.4849)	(0.3048)	(0.1789)	(0.4346)	(0.4045)	(0.5148)	(0.3641)
Exit	-0.2413***	-0.0969	-0.3439**	-0.0097	-0.3378***	-0.2668***	-0.2739*
	(0.0319)	(0.1199)	(0.1464)	(0.0829)	(0.0885)	(0.0953)	(0.1397)
Export to sales ratio	0.5294**	-0.0254	0.0237	0.1137*	0.2163	0.2184**	
	(0.2096)	(0.0694)	(0.0700)	(0.0583)	(0.1539)	(0.0854)	
HHI	-0.0249	0.5048	-0.1995	0.0437	0.1864	0.1440	-2.2467**
	(0.3483)	(0.4403)	(0.4022)	(0.2189)	(0.4628)	(0.1681)	(1.0734)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
# observations	1202	1778	1746	2223	2503	3289	1437
# firms	512	622	510	747	904	1195	660
Adjusted R^2	0.562	0.630	0.478	0.628	0.451	0.597	0.439
Residual sum of squa	47.28	28.57	27.30	33.11	83.34	47.74	52.68

Notes: Significance level at which the null hypotheses is rejected: ***, 1%; **, 5% and *, 10%. The standard errors are clustered at firm level.

Table 9: Remote access and productivity: Skill level and R&D activities across firm size

	(1)	(2)	(3)	(4)
Samples	Low skill	High skill	No R&D	Yes R&D
VARIABLES	ln(Y/L)	ln(Y/L)	ln(Y/L)	ln(Y/L)
Remote access	-0.1045***	0.0496	-0.0784***	0.1176*
	(0.0349)	(0.0439)	(0.0260)	(0.0618)
Remote access*Medium firms	0.0881	-0.0323	0.0740*	0.0175
	(0.0580)	(0.0518)	(0.0428)	(0.0593)
Remote access*Large firms	0.0956**	-0.0486	0.0641*	-0.1160*
	(0.0379)	(0.0512)	(0.0330)	(0.0630)
ln(K/L)	0.0172	0.0193	0.0085	0.0287
	(0.0190)	(0.0448)	(0.0200)	(0.0201)
ln(M/L)	0.3730***	0.3548***	0.3692***	0.5303***
	(0.0558)	(0.0649)	(0.0405)	(0.0849)
ln(L)	-0.1328***	-0.2103*	-0.1888***	0.0286
	(0.0511)	(0.1219)	(0.0415)	(0.0434)
Part-time (%)	0.0303	0.1249	0.0249	-0.6920
	(0.1031)	(0.0988)	(0.0825)	(0.6519)
Training costs per worker	0.2366	0.8030***	0.5845*	0.2323
	(0.3765)	(0.2863)	(0.3206)	(0.2454)
Social expenses per worker	0.5394*	-0.0130	0.1929	0.2728
	(0.3005)	(0.0857)	(0.1427)	(0.3063)
PC (%)	0.0187	-0.0432	0.0026	0.0010
	(0.0580)	(0.0604)	(0.0490)	(0.0526)
ln(wage)	0.3309***	0.3111***	0.3182***	0.3484***
	(0.1091)	(0.0976)	(0.0647)	(0.0909)
Males(%)	0.1816*	-0.0357	0.0615	-0.2437**
	(0.1084)	(0.1988)	(0.0952)	(0.1080)
R&D workers (%)	0.3481	-0.3347		0.5986**
	(0.2640)	(0.2583)		(0.2808)
Exit	-0.2118***	-0.1197	-0.2386***	
	(0.0744)	(0.1110)	(0.0780)	
Export to sales ratio	0.1649*	0.1167	0.1504**	0.0112
	(0.0843)	(0.1430)	(0.0729)	(0.0714)
HHI	0.0772	0.7847*	0.0003	0.7368**
	(0.2916)	(0.4735)	(0.2549)	(0.2898)
Year FE	Yes	Yes	Yes	Yes
Industry trends	Yes	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes	Yes
F-test: Total effect of remote access for mediu	-0.0164	0.0173	-0.00440	0.135
P-value	0.753	0.540	0.907	0.00314
F-test: Total effect of remote access for large f	-0.00888	0.00102	-0.0142	0.00165
P-value	0.616	0.975	0.516	0.907
# observations	3223	1503	3981	745
# firms	1478	746	1487	308
Adjusted R^2	0.492	0.464	0.512	0.723
Residual sum of squares	70.540	17.240	108.900	2.404

Notes: Significance level at which the null hypotheses is rejected: ***, 1%; **, 5% and *, 10%. The standard errors are clustered at firm level.

Table A1: Variables, measurement and source

Variables	Measurement	Source
Workplace practice		
Remote access	Indicator variable if the firm enables remote access	IUTIC
Remote access continuous	Measure of remote access intensity (remote access indicator interacted with the share of PC users in the firm)	IUTIC
Part-time (%)	Share of part-time employees	SCIE
Training costs per worker	Expenses per worker related to training, expressed in Euros divided by 10000 (prices =2016)	SCIE
Social expenses per worker	Firm expenses per worker related to maternity, family, childcare, lodging, education, work accidents, expressed in Euros divided by 10000 (prices=2016)	SCIE
Output/input variables		
Ln(Y/L)	log of sales per worker (prices =2016)	SCIE
Ln(K/L)	log of capital per employee (prices =2016)	SCIE
Ln(M/L)	log of materials per employee (prices =2016)	SCIE
Ln(VA/L)	log of value added per worker (prices =2016)	SCIE
Ln(K)	log capital (prices =2016)	SCIE
Ln(M)	log materials (prices =2016)	SCIE
Ln(L)	log of employment (prices =2016)	SCIE
Operational profits	Operational profits (prices =2016)	SCIE
Other firm variables		
PC (%)	Share of workers that use PC at least once per week	IUTIC
Export to sales ratio	Exports to sales ratio (export ratio)	SCIE
Ln(wage)	Log of average real wage (prices =2016)	SCIE
Males (%)	Share of male employees	SCIE
R&D workers (%)	Share of employees involved in R&D activities	SCIE
Exit	Indicator variable if the firm leaves the market	SCIE
HHI	Herfindahl-Hirschman sales index defined at 5 digit level of economic activity	SCIE

Table A2: Distribution of firms according to remote access (RA) status in each industry

	Adopters	Abandoners	Always RA	Never RA	Total
Food and beverages	20	9	91	10	130
Textile, clothing and leather	22	11	47	11	91
Wood, paper and printing	11	3	33	1	48
Quimicals, farmaceutical and rubber	9	2	69	3	83
Minerals and metalic products	13	8	78	5	104
Equipments production	21	18	85	10	134
Transport equipments	14	16	57	9	96
Other manuacturing	12	6	32	8	58
Electricity, water and garbige	9	9	37	2	57
Construction	9	5	94	3	111
Car production and repair	10	4	59	3	76
Wholesale trade	49	22	178	6	255
Retail trade	9	2	75	4	90
Transportation and storage	1	3	42	1	47
Hotels and restaurants	11	17	58	20	106
Cinema, radio, tv	2	3	15	0	20
Telecommunications	0	6	26	2	34
Real estate	2	1	4	0	7
Consulting and other	0	0	9	0	9
Other services	6	19	60	3	88
# firms	230	164	1149	101	1644

Table A3: Distribution of firms according to remote access (RA) status for different firm categories

		Adopters	Abandoners	Always RA	Never RA	Total
Size	Small	89	95	249	79	512
	Medium	95	31	478	18	622
	Large	46	38	422	4	510
R&D	No	208	152	954	100	1414
	Yes	22	12	195	1	230
Skills	Low	152	123	605	85	965
	High	78	41	544	16	679
Export status	Yes	82	70	347	64	563
	No	148	94	802	37	1081
	# firms	230	164	1149	101	1644

Table A4: Summary statistics – full sample

	Obs	Mean	Std. Dev.	Min	Max
Remote access	4726	0.8652	0.3415	0	1
Remote access (continuous)	4726	0.4391	0.3251	0	1
ln(Y/L)	4726	12.1084	1.4021	5.2643	19.7989
ln(K/L)	4726	9.9373	1.7399	0.6217	17.2197
ln(M/L)	4726	11.1152	2.2300	-2.7178	19.6587
ln(L)	4726	4.7899	1.6256	0	10.1138
Part-time (%)	4726	0.0316	0.1206	0	1
Training costs per worker	4726	0.0085	0.0272	0	1.0191
Social expenses per worker	4726	0.0304	0.0691	0	0.8587
PC (%)	4726	0.4922	0.2985	0	1
ln(wage)	4726	9.7037	0.4979	6.4067	12.9425
Males(%)	4726	0.6457	0.2525	0	1
R&D workers (%)	4726	0.0101	0.0495	0	1
Exit	4726	0.0028	0.0524	0	1
Export to sales ratio	4726	0.2532	0.3294	0	1
HHI	4726	0.0992	0.1400	0.0008	0.9809

Table A4.1: Summary statistics – small firms (L<50)

	Obs	Mean	Std. Dev.	Min	Max
Remote access	1202	0.7038	0.4568	0	1
Remote access (continuous)	1202	0.4538	0.3887	0	1
ln(Y/L)	1202	12.4284	1.9366	7.7832	19.7989
ln(K/L)	1202	9.6500	1.9885	0.6217	17.2197
ln(M/L)	1202	11.5367	2.6491	0.0000	19.6587
ln(L)	1202	2.5918	1.0381	0	5.4889
Part-time (%)	1202	0.0166	0.0806	0	1
Training costs per worker	1202	0.0061	0.0365	0	1.0191
Social expenses per worker	1202	0.0132	0.0603	0	0.8587
PC (%)	1202	0.5902	0.3185	0	1
ln(wage)	1202	9.6591	0.6158	6.4067	12.9425
Males(%)	1202	0.6587	0.2431	0	1
R&D workers (%)	1202	0.0115	0.0736	0	1
Exit	1202	0.0008	0.0288	0	1
Export to sales ratio	1202	0.1614	0.2790	0	1
HHI	1202	0.0891	0.1304	0.0008	0.9688

Table A4.2: Summary statistics – medium-sized firms (50≤L<250)

	Obs	Mean	Std. Dev.	Min	Max
Remote access	1778	0.9016	0.2980	0	1
Remote access (continuous)	1778	0.4749	0.3127	0	1
ln(Y/L)	1778	12.4024	1.0889	5.2643	16.2174
ln(K/L)	1778	10.3268	1.3705	3.6000	14.2644
ln(M/L)	1778	11.6050	1.8006	1.0595	16.1989
ln(L)	1778	4.8176	0.5105	2.6391	6.9007
Part-time (%)	1778	0.0104	0.0573	0	0.977
Training costs per worker	1778	0.0109	0.0282	0	0.5408
Social expenses per worker	1778	0.0349	0.0715	0	0.7186
PC (%)	1778	0.5081	0.2866	0.003	1
ln(wage)	1778	9.7942	0.4144	7.4673	11.1400
Males(%)	1778	0.6830	0.2161	0.0065	1
R&D workers (%)	1778	0.0099	0.0454	0	0.7963
Exit	1778	0.0034	0.0580	0	1
Export to sales ratio	1778	0.2366	0.3098	0	1
HHI	1778	0.0873	0.1159	0.0008	0.8755

Table A4.3: Summary statistics – large firms (L≥250)

	Obs	Mean	Std. Dev.	Min	Max
Remote access	1746	0.9393	0.2389	0	1
Remote access (continuous)	1746	0.3926	0.2812	0	1
ln(Y/L)	1746	11.5886	1.0515	6.6174	15.5747
ln(K/L)	1746	9.7383	1.8199	0.9340	14.2235
ln(M/L)	1746	10.3262	2.0841	-2.7178	15.4732
ln(L)	1746	6.2749	0.7828	4.1744	10.1138
Part-time (%)	1746	0.0635	0.1730	0	0.986
Training costs per worker	1746	0.0078	0.0165	0	0.2484
Social expenses per worker	1746	0.0377	0.0704	0	0.7131
PC (%)	1746	0.4085	0.2718	0.0014	1
ln(wage)	1746	9.6424	0.4711	7.8514	11.0146
Males(%)	1746	0.5989	0.2840	0.0069	1
R&D workers (%)	1746	0.0093	0.0286	0	0.3022
Exit	1746	0.0034	0.0585	0	1
Export to sales ratio	1746	0.3335	0.3606	0	1
HHI	1746	0.1184	0.1646	0.0008	0.9809

Table A5: Distribution of firm-year observations

# of years a firm appears		Observations		Firms	
2		1442	31%	721	44%
3		1224	26%	408	25%
4		2060	44%	515	31%
	Total	4726		1644	