CESifo

CONFERENCES 2019

The Effects of the Digital Transformation on the Workplace and the Labor Market

Does Remote Work Improve or Impair Firm Labour Productivity? Longitudinal Evidence from Portugal

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20 YEARS CESifo

Does remote work improve or impair firm labour productivity? Longitudinal evidence from Portugal*

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November 2019

Abstract

Whether or not the use of remote work increases firm labour productivity is theoretically ambiguous. We use a rich and representative sample of Portuguese firms, and within-firm variation in the policy on remote work, over the period 2011-2016, to empirically assess the causal productivity effect of remote work. Our findings from estimations of models with firm-fixed effects suggest that the average productivity effect of allowing remote work is significantly negative, though relatively small in magnitude. However, we also find a substantial degree of heterogeneity across different categories of firms. In particular, we find evidence of opposite effects of remote work for firms that do not undertake R&D activities and for firms that do, where remote work has a significantly negative (positive) effect on labour productivity for the former (latter) type of firms. Negative effects of remote work are also more likely for small firms that do not export and employ a workforce with a below-average skill level.

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

JEL Classification: D24; L23; M54.

*This paper is financed by National Funds of the FCT – Portuguese Foundation for Science and Technology within the project "UID/ECO/03182/2019". We thank *Instituto Nacional de Estatística* for allowing access to data from *Sistema de Contas Integrado das Empresas* and *Inquérito à Utilização de Tecnologias da Informação e da Comunicação nas Empresas.* We also thank seminar participants at Örebro University and NIPE for valuable comments.

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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' (henceforth RW) 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 (Eurofound, 2017; OECD, 2016). 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.

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 RW (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] Regarding the effect on productivity (at worker or firm level), whereas the empirical evidence overwhelmingly points to a positive effect of RW, recent lab experiments provide evidence of negative or, at best, mixed

[1] See for example the surveys by Bailey and Kurland (2002), Gajendran and Harrison (2007) and Allen et al. (2015).

effects of telework on productivity. Novel theoretical developments also show that the relationship between self-managed working time (which includes RW), 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 empirically study the impact of remote use on firm labour productivity using firm-level data for Portugal, a country where the prevalence of telecommuters is higher than the EU-28 average. We gather information from the *Community Survey on ICT Usage and E-Commerce in Enterprises* (Eurostat, 2011) during the 2011-2016 period. This survey on the information and communication technology (ICT) usage in enterprises contains the following question: 'Did your enterprise provide to the persons employed remote access to the enterprise's e-mail system, documents and applications?'. We use the reported answer to this question as a proxy for the RW use in the firm (or, more precisely, an upper bound on the propensity of the firm to allow their employees to work remotely). This survey is then matched with data from the Portuguese *Integrated Business Accounts System* to recover data on firm characteristics.

Our data allow us to make several contributions to the literature. First, the panel structure of the dataset improves upon the vast majority of empirical studies that are based on cross-sectional data. In particular, this feature combined with the within-firm variation in the use of RW allows us to control for firm-fixed heterogeneity. We are then able to circumvent some potential endogeneity problems and thus to interpret our findings as being causal. Second, the representativeness of the data allows us to look at the effects over the entire firm size distribution and across industries. These two dimensions are not examined in previous work that looked at non-random or selected samples (usually large firms and in manufacturing). Third, since the panel includes firms that either adopt or abandon the practice, we are able to check if the effect is symmetric or not. Fourth, the richness of the data allows us explore the possibility of heterogeneous effects of RW along several different dimensions related to firm, worker and job characteristics, and it also allows us to evaluate if and how results are sensitive to modifications in the definitions and measurements of our key variables. Finally, the use of diverse measures of technology also allows us to contribute to the literature on the effects of ICT on productivity.

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

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

Lynch, 2004; Bloom et al., 2011, 2019). As a starting point, we estimate a specification without firm-fixed effects and find a positive relationship between RW adoption and labour productivity. This is however a naïve approach, since a statistically significant correlation might be caused by systematic variation in unobserved variables. Indeed, once we control for time-invariant firm-level heterogeneity, the sign of our key estimate reverses, indicating that RW has a significantly negative effect on firm labour productivity. This result is particularly interesting in the light of the fact that a large portion of the existing empirical literature on the effect of RW is based on cross-sectional evidence.

However, our subsequent analysis reveals that this average effect estimated for the full sample of firms masks a considerable degree of heterogeneity. More specifically, we find that the negative productivity effect of RW 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. Furthermore, this effect is primarily identified by firms that adopted, rather than abandoned, a policy of allowing remote work during the period of observation. A negative effect of RW on labour productivity is also generally more pronounced when we use sales per worker (instead of value added per worker) as the measure of firm labour productivity.

On the other hand, we also identify positive productivity effects of RW for some subcategories of firms, in particular for firms that undertake some R&D activities. The finding of significantly opposite effects of RW depending on the R&D status of the firm has intriguing parallels to previous experimental evidence showing that remote work affects productivity differently for 'routine' versus 'creative' job tasks (Dutcher, 2012).

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 main analysis, including robustness checks and several extensions, is given in Section 5. Finally, Section 6 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 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 RW and 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, RW 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 (CSR), 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 RW 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 RW or any other high-performance work practice (e.g., Black and Lynch, 2004; Cappelli and Neumark, 2001). 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 RW on firm productivity concerns workers' psychological well-being and motivation (OECD, 2007). RW 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. RW can thus lead to increased firm productivity through individual channels (see, e.g., Allen et al., 2015; Beauregard and Henry, 2009; Bloom et al., 2011; Bloom and Reenen, 2011; Edmans, 2012).

Finally, the promotion of employee- and family-friendly work practices can be an expression of CSR, and the debate about the value creation of CSR is still ongoing. On the one hand, CSR allows firms to take a longer-term perspective on their activities and in doing so maximize 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 (Beckmann et al., 2017; Ellingsen and Johannesson, 2008).

While these arguments are mostly in favour of the positive impact hypothesis, several channels exist through which RW can negatively influence worker and firm performance. Therefore, while allowing for RW 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 CSR argument. Additionally, RW 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).

The model of Beckmann et al. (2017) captures the potential trade-off involved in a firm when RW 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 selfmanagement of time by workers, which under an imprecise monitoring of effort, can lead to lower productivity. This effect is however counteracted by instrinsic motivation of workers. Consequently, the net effect on worker effort, and in turn firm productivity, is *a priori* ambiguous.

2.2 Empirical evidence

There is a vast and growing empirical debate on the linkages between RW and several *individual-level worker outcomes*, such as turnover intention, absenteeism, job autonomy and commitment, job satisfaction, and work-family conflict management. The evidence on these linkages that potentially affect firm productivity is however inconclusive. Bailey and Kurland (2002) do not find increases in job satisfaction in their survey, whereas Gajendran and Harrison (2007) review empirical evidence on the effect of telecommuting on different personal or work related outcomes and report overall positive effects. The more recent review by Allen et al. (2015) presents more mixed evidence: only modest or even non-existent effects have been identified in terms of RW allowing workers to better manage family relations. In contrast, Wheatley (2017) and Kröll and Nüesch (2019) find positive effects on job and leisure satisfaction for British and German workers, respectively, when using large representative surveys of the population.

Concerning *individual-level worker productivity*, the survey by Bailey and Kurland (2002) reports an increase after the introduction of RW, though most studies reviewed use self-reported data. More recently, Bloom et al. (2015) find a positive and significant impact of RW 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, employees working from home reported more job satisfaction and the company experienced an increase in several productivity measures (number of calls made and minutes worked per shift).

On the other hand, evidence from lab experiments points to potential non-positive effects of RW on individual-level productivity. 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 RW would decrease productivity. Additionally, RW 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 RW 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 RW, there is no effect of RW on individual productivity.

The work that uses firm-level data to assess directly the effect of RW on *firm-level productivity* is scarce and fragmented. One strand of the empirical literature looks simultaneously at the effect of multiple human resource and management practices when these are summarised (typically) in one or more firm-level indices.[3] In a related strand, the focus in on the separate (partial) effects of different human management practices and/or the effect of combined practices (often through ad-hoc interactions), often referred to as *bundles* of practices.[4] The idea of the bundle approach is that there might be complementarities among different human resource practices, implying that the effect of a bundle might be larger than the sum of the partial effects of different practices.

The overall message that emerges from the former literature is reasonably clear. Human resource management systems (measured by firm-level indices) lead to positive and statistically significant effects on firm productivity (though Bloom et al., 2011, detect no significant impact). An important feature of this literature is that the studies are either cross-sectional (often not representative) and/or are based on a single industry or a specific firm size (usually large firms).

Research that focuses on the separate effects of different human resource management practices often (but not always) includes RW in the list of practices. This literature also points to a positive association between RW and different measures of business productivity. Meyer et al. (2001) finds a positive correlation between the prevalence of RW and profits when using non-representative US data, whereas Martínez-Sanchez et al. (2008) report a similar result for a small sample of 156 Spanish firms. Whyman et al. (2015) provide evidence on an analogous RW effect, but only in non-unionised UK workplaces.

The empirical evidence also supports the hypothesis that bundles, rather than individual prac-

[3] 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).

[4] Studies focussing on separate effects of different human management practices include, e.g., Meyer et al. (2001), Combs et al. (2006), Martínez-Sanchez et al. (2008) and Whyman et al. (2015), whereas Perry-Smith and Blum (2000), Cappelli and Neumark (2001) and Black and Lynch (2001, 2004), also consider bundles of work practices.

tices, have stronger effects on different measures of productivity, as documented by Combs et al. (2006) in their meta-analysis study. Although RW is not included in the bundle literature, some important patterns emerge from it. First, the bundle literature which largely uses cross-sectional data also points to a positive effect of some bundles, depending on the characteristics of the firm (Black and Lynch 2001). Second, some work that uses both cross-sectional and long-differenced data shows that the differenced data weaken the cross estimates. This result is then consistent with the existence of a positive correlation between unobservable factors and the adoption of human resource management practices (Cappelli and Neumark, 2001).

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.[5] 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 working outside the formal working place. More specifically, as a proxy for remote work at firm level, we use the answer to the following question: 'Did your enterprise provide to the persons employed remote access to the enterprise's e-mail system, documents and applications?'.[6] 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 that are crucial for our empirical analysis. These variables include the share of workers who use a personal computer (PC) at least

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

[6] Although the question refers to 'remote access' and not explicitly to remote work, it seems reasonable to consider the frequency of positive answers to this question as an upper bound on the propensity of firms to allow remote work.

once per week, the share of workers who use a PC with internet access at least once per week, the share of workers who use a portable computer (laptop) with internet use access, and finally, an indicator variable for high speed internet usage.

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.

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, regional location and a firm death indicator.[7] In addition, the dataset includes workforce characteristics such as gender distribution, share of part-time workers and share of unpaid 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 whether the firm is involved in research activities, and whether the firm is engaged in international trade through import or export activities. These and other variables used in the empirical analysis are described in Table A.1 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 6915 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 1610 firms, among which 1118 (98) always (never) give their employees the possibility to engage in remote work in any year during the period of analysis. Among the remaining 394 firms, 230 do not allow RW in the first year they appear in the dataset but adopt the policy in a later year, whereas 164 firms abandon the practice of RW after employing it in the first year of observation.[8] 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 the RW practice as the source of identification.

Given the sampling design of the IUTIC survey, it should be noted that our final sample is

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

[8] From the initial sample of 8525 firms, we had already excluded firms that change the RW practice more than once during the period of analysis.

biased towards larger firms, since the sample includes the population of large firms, whereas the remaining firms are randomly chosen within size categories in each industry. 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 5.2. Second, as one of several extensions to our main analysis, we explore the possibility of heterogeneous effects across different firm sizes (in Section 5.3).

In Table 1 we report the mean values of the variables, averaged over all firm-year observations in which remote work was allowed, 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 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 are more likely to opt for RW also allow part-time work, 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 (60%-80%) and statistically significant, whether measured by sales per worker or value added per worker, suggesting that the adoption of RW is associated with higher firm labour productivity. Additionally, Figure 1 shows that the productivity distribution of firms that use RW lies to the right of the equivalent distribution of those that do not use RW. This evidence corroborates 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 inputs use. Firms that adopt RW use much more capital and materials per worker, suggesting that these firms tend to be larger, which is confirmed by the significantly higher proportion of large and medium-sized firms observed for this group. This finding supports the view that large firms tend to adopt work-life practices to a larger 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 opt for RW employ a relatively larger proportion of workers that use PC, a larger share of workers that use PC with internet, and use internet with a faster speed. Furthermore, these firms also employ a higher share of workers involved in R&D activities, and their workforce is, on average, more educated (proxied by the average wage paid by the firm) and paid above the mean industry level. Taken together, this evidence indirectly suggests that firms that allow RW also employ a higher share of skilled workers.

In terms of gender composition of the workforce, the values in Table 1 indicate that firms that allow remote work also employ a higher proportion of men. This evidence contradicts 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., Bloom et al., 2011, and Konrad and Mangel, 2000).

The values reported in Table 1 also indicate that the adoption of RW is positively associated with the degree of international trade exposure, 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, RW firms 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 normalised (on labour) production function:

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

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.[9] Furthermore, RW_{it} is an indicator variable that identifies if, at time t, firm i allows remote work, 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 with a PC, the share of workers with a PC with internet access, and the internet speed. Third, we control for other workforce characteristics by including the share of male workers, the share of unpaid workers, the share of workers involved in R&D activities, and the average level of skills of the firm (proxied by the average wage and an indicator variable if the firm pays above the industry mean). Fourth, we account for differences in product market competition, measured by the Herfindahl-Hirschman Index, and exposure to international trade, measured by the export and import to sales ratios. Finally, we include a group of control variables that account for firm size and exit from the market, economic activity (13 industries) and location defined at the NUTS2 level for Portugal (6 regions). 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.[10]

A potential criticism of our empirical strategy concerns the timing of the impact of RW. Our specification assumes that the effect of RW 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 reasons. First, the short length of our unbalanced panel data would imply a large loss of firms and observations. Second, and most

[9] Notice that, by including (log of) labour as an independent variable, we allow for the possibility of non-constant returns to scale.

[10] 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).

importantly, the RW and output variables refer to two different points in calendar time each year. According to the IUTIC survey, the RW 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 introducing (or abandoning) RW.

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 allow and firms that do not allow RW 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 productivity effect of RW is based on within-firm changes in RW use 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 either adopt or abandon RW during the period of observation) are compared to untreated firms (i.e., firms that never or always allow remote work).

Second, our results may still be subject to omitted variable bias, such as demand shocks that affect both RW use and firm labour productivity. Alternatively, some firms might simultaneously adopt RW 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.

In the next section we will present results from a set of different regressions, where we estimate in turn a series of equations ranging from a simplified version of (1) to our most comprehensive specification, where we add firm-fixed effects and industry-specific time trends to the full equation given by (1). The latter constitutes our most preferred empirical model.

In an extension to our main empirical analysis, we will also further address the issue of endogeneity by combining a difference-in-differences approach with propensity score matching (DD-PSM).

The propensity score is the predicted probability of a firm adopting (or abandoning) remote work as a function of firm attributes observed one year before the treatment occurs. Given that in our sample we have firms that either adopt or abandon RW, we estimate separately a single model for each type of treatment. We then match firms that adopt RW with firms that never adopt RW, and firms that abandon RW with firms that always employ RW. We perform exact matching of firms by size, year, industry and region, using one-to-one nearest-neighbour without replacement and imposing common support. By using DD-PSM we essentially inspect for divergence in the productivity path between firms that adopt (abandon) RW and matched control firms that had similar observable attributes in the year prior to the treatment. This analysis is provided in Section 5.3.4 below.

5 Results and discussion

We present our empirical results in three stages. First, we 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 and alternative definitions of key variables. Finally, we re-estimate our preferred model using several different partitions of the data. These extensions of the main analysis allow us to uncover potentially heterogeneous effects of remote work.

5.1 The effect of remote work on 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 and RW is defined as an indicator variable. The first three 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 industry-, region- and time-fixed effects are added to the basic Cobb-Douglas specification, whereas the subsequent two columns show estimation results with further controls included. More specifically, control variables capturing the effects of other human resource management practices (share of part-time workers, and training costs and social expenses per worker) are added in Column 2. A series of further controls are added in Column 3, capturing differences in firm size, ICT diffusion, workforce size and composition, firm exit, international trade exposure and product market competition.

[Table 2]

Regarding our main variable of interest – the use of remote work – the estimates from the first two columns indicate a positive and statistically significant association between remote work adoption and labour productivity, although the magnitude of the effect declines marginally when other human management practices are taken into account. This evidence corroborates earlier findings 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 3, the positive effect of RW loses its statistical significance when we include the full set of control variables. Thus, when we rely mainly on cross-sectional variation to identify the effect of RW, our results are qualitatively similar to 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 effect of our main variable of interest is *reversed*, and we find that RW has a *significantly negative* impact on firm labour productivity. Our estimates indicate that the use of RW leads to a reduction in labour productivity of more than two percent. This estimated effect is practically identical whether we include industry-specific time trends (Column 5) or not (Column 4).

As for the effects of other explanatory variables, the evidence based on cross-sectional variation suggests that labour productivity is consistently higher in medium-sized and small firms, in firms with a higher-skilled workforce (proxied by the average wage), and in firms that operate in more concentrated industries, but all these effects vanish when we include firm-fixed effects. Among the variables that control for ICT diffusion, only the share of PCs with internet access appears to be statistically significant. Interestingly, conditional on the skill level, there is no significant association between gender and labour productivity, which corroborates earlier research in several advanced economies (e.g., Bloom et al., 2011). Finally, the significantly negative estimate of the coefficient on (log of) labour inputs suggests that the 'average' technology is characterised by decreasing returns to scale.

5.2 Robustness

In the following we test the robustness of the results from our most preferred model, given by the estimates reported in Column 5 of Table 2. Thus, all of our subsequent robustness checks are based on the most comprehensive version of (1), with firm-fixed effects and industry-specific time trends added.

5.2.1 RW measurement and sampling weights

In our benchmark analysis we measure the use of RW as an indicator variable, implying that each firm is classified as either allowing remote work or not. However, the adoption of an RW policy might have different effects across different firms depending on the share of the workforce to which this policy applies. 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.[11] By interacting this share with the RW indicator, we obtain a continuous measure of RW.[12]

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.[13]

[Table 3]

The results from both of these 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. We see that, in qualitative terms, our main result is robust to the use of a continuous RW measure and to the use of sampling weights. Moreover, the magnitude of the estimated coefficient increases when using a continuous RW measure or when using sampling weights, and it increases even more when using

[11] Notice that the survey question which our definition of the RW variable is based on refers to 'remote access to [...] e-mail system, documents and applications', which effectively means that RW is restricted to computer-based work.

[12] Results remain qualitatively similar if the continuous (remote work) variable is defined alternatively as the interaction between the RW indicator and the share of workers that use PC with internet access.

[13] 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.

both.[14] These results suggest that (i) the adverse productivity effects of RW increase with the share of workers included by the policy, and that (ii) the effect of RW is heterogeneous across different-sized firms.

5.2.2 Managerial effects

In our preferred model, with firm-fixed effects, identification of an RW effect is based on within-firm variation in RW policy; in other words, the effect is identified by firms that either adopt or abandon an RW policy during the period of analysis. However, it might be the case that a change in RW policy coincides with other changes at the firm that could have an impact on productivity, thereby confounding the estimated effects of RW. More specifically, a change in RW policy 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 estimates that correspond to the previously reported estimates from our benchmark model.[15] If we control for managerial quality, we see that the RW coefficient remains very similar both in magnitude and statistical significance, which is reassuring for the robustness of the results.

5.2.3 Alternative productivity measures

As a final robustness check, we examine whether RW 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.

[14] The estimate reported in the last column of Table 3 suggests that the adoption of an RW policy that applies to the entire workforce reduces labour productivity by close to 10 percent on average.

[15] These estimates are slightly different in magnitude compared to the estimates in the last column of Table 2. This is caused by a smaller sample size due to missing data on managerial compensation.

[Table 5]

We re-estimate the most comprehensive version of (1) using these alternative productivity measures, and using both the binary and the continuous measures of RW in separate regressions. The resulting estimates are reported in Table 5. Although all the point estimates are negative, indicating that RW might have a negative effect on both outcomes, they are much less precisely estimated than in the benchmark regression, particularly when using operational profits as the outcome variable.

5.3 Heterogeneous effects

We complete our analysis by making a number of different partitions of the data in order to uncover potentially heterogeneous effects of RW along one or more dimensions. For each partition, we estimate the most comprehensive version of (1) using both the binary and the continuous measures of RW in separate regressions. Furthermore, in addition to our benchmark measure of labour productivity (i.e., sales per worker), we also report results using value added per worker as an alternative productivity measure.

5.3.1 Firm size

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. The results, reported in Table 6, reveal that our previously derived adverse effect of RW on labour productivity is mainly driven by small firms. For this subset of firms, we find a statistically significant negative productivity effect of RW regardless of how this policy is measured (binary or continuous) and regardless of how labour productivity is measured (sales per worker or value added per worker). And in all cases, the magnitude of the adverse productivity effect is considerably larger than the corresponding estimate obtained using the full sample of firms.

[Table 6]

For medium-sized firms, on the other hand, we find that RW has a significantly *positive* effect on productivity (at least when measured by sales per worker), though these effects are much smaller in magnitude than the negative effects found for smaller firms. Finally, for large firms, all the relevant point estimates are close to zero, and none of them are statistically significant.

Overall, our results suggest that the productivity effects of RW are strongly heterogeneous across firm size. In *quantitative* terms, the effect of RW is decreasing with firm size, whereas, in *qualitative* terms, the effect of RW appears to be non-monotonic, with large negative effects for small firms and smaller but positive effects for medium-sized firms.

5.3.2 Industry type and export activities

In Table 7 we report the estimated effects of RW when firms are split according to two broad categories of industry affiliation: services and manufacturing. These results suggest that the adverse productivity effect of RW is somewhat more driven by firms operating in service industries, though the reported p-values show that, for both productivity measures, the estimated RW coefficients for manfacturing and service firms are not significantly different from each other.

[Table 7]

In Table 8 we report the corresponding estimates when firms are classified according to whether or not they engage in export activities. Once more, we find strong evidence of heterogeneity, as the estimates given in Table 8 clearly show that the results are different for exporters and non-exporters. For the latter category of firms, the effect of RW is significantly negative, and large in magnitude, regardless of how RW and labour productivity are measured. For exporters, on the other hand, we find no statistically significant productivity effects of RW.

[Table 8]

5.3.3 Worker and job characteristics

Our next partitions of the data are made according to criteria that allows us to investigate if the effects of RW are somehow related to worker and/or job characteristics. First, we 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. 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.

[Table 9]

The estimated effects of RW when firms are categorised according to skill level are presented in Table 9, and these results clearly indicate that skill level might be a relevant factor. With our benchmark productivity measure, a significantly negative effect of RW is found only for the sample of low-skill firms. For the high-skill firms, on the other hand, the point estimates are positive, though not statistically significant. For the alternative productivity measure we find no statistically significant effects, though the signs of the point estimates suggest a similar pattern, being negative (positive) for low-skill (high-skill) firms.

The above described results can perhaps 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. In a similar vein, our results could also be interpreted in the light of 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. Such effects might be captured by considering the skill-level of the firm, if there is a positive relationship between the share of high-skilled workers and the share of creative tasks, which seems a plausible assumption.

However, the distinction between routine and creative tasks is perhaps even better captured by considering yet another partition of the data, which is arguably more directly related to job characteristics, namely a distinction 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.

[Table 10]

The estimation results with this particular partition of the data are shown in Table 10. When using our benchmark productivity measure (Panel A), these results are quite striking. In the subset of firms that do not undertake R&D, which is the large majority of firms, remote work has a significantly negative effect on labour productivity. However, for the other type of firms, in which some R&D activities are performed, the effect of RW on productivity is significantly *positive*. And the magnitude of the effects are quite similar (though with opposite signs) for both categories of firms. When using the alternative productivity measure (Panel B), the signs of the point estimates once more follow a similar pattern, though without being statistically significant.

5.3.4 Adoption and abandonment of remote work

As previously explained, the identification of the RW effect in our most preferred empirical specification is based on the observation of firms that change their RW policy over time; firms that either adopt or abandon a policy of allowing (some or all of) their employees to work from home. Our full sample comprises 230 firms that adopt and 164 that abandon RW during our period of observation. In our final partition of the data, we explore if the effect of RW varies across these two categories of firms.

[Table 11]

The results, displayed in Table 11, suggest that the effect of RW differs not only across firms that adopt and abandon the policy, but also across the two different productivity measures. The most conspicuous type of heterogeneity is probably the former, since *adoption* of RW leads to a statistically significant productivity loss regardless of which labour productivity measure we use. This suggests that the adverse productivity effect of RW found in our benchmark estimation appears to be mainly driven by firms that adopt this policy during our period of analysis. However, although *abandonment* of the same policy does not seem to have any significant effects on productivity, it is worth noticing that the point estimates for the two different productivity measures have different signs, and the reported p-values show that the estimated effect of RW on our benchmark productivity measure (sales per worker) is not statistically different for adopters and abandoners.

[Table 12]

We further explore this issue by showing the results obtained with a matched sample, using the propensity score matching approach described in Section 4. In Table 12 we report the results from the estimation of the propensity score for both treatments: adoption and abandonment of RW. In addition to industry-, region- and year-fixed effects, both models include, as explanatory variables, lagged values (in logs) of sales, sales per employee, capital, average wage, as well as sales growth rate and capital per employee growth rate. The results show, not surprisingly, that the decision of whether to adopt or abandon RW is driven by different factors. Compared to firms that do not allow remote work, RW adoption is more likely for firms with more capital, a higher growth rate of capital per employee, and a higher worker skill level (proxied by the average wage). On the other hand, compared to firms that allow remote work, abandonment of RW is more likely for firms with lower levels of sales, sales growth, capital and worker skills.[16] As expected, the matching procedure leads to a considerable reduction in the size of our sample, which implies that the subsequently derived results should be interpreted with some caution. We are able to successfully match 140 firms that change RW policy during the period of observation. Among these firms, there are 35 adopters and 105 abandoners.

[Table 13]

Our estimation results based on the matched sample are presented in Table 13. These results suggest that the main dimension of heterogeneity is between adopters and abandoners, and not so much across different productivity measures. For the subset of firms that adopted an RW policy during the period of observation, these results strongly confirm the pattern detected when using the full sample, as shown in Table 11. Adoption of RW is associated with a significant reduction in labour productivity, and this conclusion does not depend on whether labour productivity is measured by sales per worker or value added per worker. Moreover, the magnitudes of the estimated effects are considerably larger for the matched sample than for the benchmark sample.

For the other subset of firms, the ones that abandon the use of remote work, the point estimates of the RW effect are positive for both productivity measures, as in Table 11, and these coefficients are now significantly different from the ones estimated for firms that adopts RW, as evidenced by the reported p-values. Furthermore, the effect of RW for abandoners is now also statistically significant when we use our alternative productivity measure. Thus, based on our matched sample, any change in RW policy, whether introducing or abandoning the possibility of remote work, is found to have a negative effect on value added per worker.

5.4 Discussion

The main result from our benchmark analysis, reported in the last column of Table 2, is that a policy of allowing employees to work from home has a significantly negative effect on firm labour

[16] In Tables A2-A4 in the Appendix we report results from several additional tests of matching quality, such as individual t-tests for each variable, the Pseudo R2 of the probit on the matched data, and the test of joint significance of regressors given by the Chi-square test. Taken together, all these tests provide evidence that the matching procedure succeeds in removing observable differences between the treated and untreated firms.

productivity. However, our subsequent analysis has revealed that the estimated average effect masks a substantial heterogeneity across different types of firms. In short, the negative productivity effect of RW seems to be mainly driven by small firms that do not export, that do not undertake any R&D activities, and that employ a relatively high share of low-skilled workers.

For some of these characteristics, such as firm size and export status, it is hard to identify a direct mechanism that could influence the effect of remote work on firm labour productivity. For other characteristics, however, the existing literature gives us some indications of how our heterogeneous effects could be explained. For example, our findings regarding the skill level and R&D intensity of firms have clear parallels to the effects of remote work on routine versus creative tasks highlighted by Dutcher (2012). In order to assess the relative importance of these two dimensions of firms characteristics – average worker skill level and presence of R&D activities – we de-compose our previously derived results (Tables 9-10) according to firm size (small, medium and large). The results presented in Table 14 allow us to assess the importance of firm skill type (Panel A) and R&D activities (Panel B) for a given category of firm size, and vice versa.

[Table 14]

The picture emanating from the results in Table 14 is quite illuminating. In Panel A we see that firm size makes a significant difference to the productivity effect of RW only for low-skilled 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 Panel B show that the negative effect of RW only applies for the subset of small firms that do not perform R&D. For the rest of the small firms, the effect of RW is significantly *positive* (if we use a continuous RW measure). Among the firms that undertake R&D activities, we also detect significantly positive effects of RW for medium-sized and large firms, which suggests that firm size is not particularly relevant in explaining the productivity effects of RW for this subset of firms.

Overall, we believe that the results shown in Table 14 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.[17] In the same vein, the importance of export status, as shown

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

in 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).

As the above discussion indicates, there is a considerable degree of subsample overlap across the different firm characteristics that are conducive to a negative productivity effect of RW, 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 250 firms that have all these four characteristics, and 105 of these firms changed RW status 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 effect of RW on firm labour productivity. Using a binary measure of RW, we find that allowing for the possibility of remote work in these firms leads to a productivity loss of almost 19 percent. If we instead use our continuous RW measure, the estimated productivity loss increases to more than 37 percent.[18] The size of these effects, which are considerably larger in magnitude than the corresponding estimates for any other subsample previously reported, give further indication that the negative average effect of RW on firm labour productivity is strongly driven by a subsample of firms with a particular set of characteristics.

6 Concluding remarks

The possibility of working remotely is understood in the human resource management literature as contributing to job satisfaction and worker motivation. It can thus be interpreted as productivity-enhancing and ultimately benefitting firm performance. Although the vast majority of empirical evidence has confirmed this hypothesis, previous work often focuses on a single firm or industry, or relies primarily on cross-sectional variation in the use of remote work. Our study broadens the scope of the analysis by using a longitudinal panel dataset of firms in a sample that is representative of the whole economy, including manufacturing and services industries. Crucially, the existence of within-firm variation in the use of remote work allows us to estimate models with firm-fixed effects, which in turn enables us to identify causal effects with a higher degree of confidence.

The importance of our empirical strategy is highlighted by our results. If we do not control for non-observable constant characteristics of the firm, we find that working from home is positively

share is almost 20 percent.

[18] Further details are available upon request.

correlated with firm labour productivity, measured by sales per worker. However, once we control for non-observable and time-invariant factors, this effect is reversed. Based on the full sample of firms, our estimates from models with firm-fixed effects suggest that remote work has a significantly negative effect on labour productivity, though the productivity loss is relatively modest in magnitude (around 2.3 percent).

However, our extended empirical analysis also reveals a substantial degree of heterogeneity in the productivity effect of remote work across different sub-samples of firms. More specifically, the negative average effect is mainly driven 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 analysis 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 work has a significantly *positive* effect on labour productivity. This suggests that the productivity effects of remote work 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 the share and characteristics of the workforce that are allowed to do remote work in a firm, and the characteristics of their jobs. This drawback is to some extent remedied, though, by the available information about the exact number of workers in each firm who use computers in their jobs, which allows us to compute a continuous proxy for the extent of remote work in a firm. 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 causal effect of remote work on firm labour productivity. In particular, we believe that our analysis provides potentially important insights about which firm characteristics that are conducive to a positive or negative productivity effect of remote work.

Appendix

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

[Table A1]

Tables A2-A4 contain additional tests of matching quality resulting from the propensity score estimations described in Section 5.3.4. In Tables A2-A3 we report individual t-tests for each variable, whereas in Table A4 we show the Pseudo R2 of the probit on the matched data, and the test of joint significance of regressors given by the Chi-square test.

[Tables A2-A4]

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Table 1 – Mean values for firms that adopt and do not adopt RW

Variables	RW	no RW	difference
Part-time (%)	0.0322	0.0298	0.0024
Training costs per worker	0.0092	0.0034	0.0058 ***
Social expenses per worker	0.0337	0.0098	0.0239 ***
ln(Y/L)	12.1769	11.6404	0.5365 ***
ln(VA/L)	10.5058	10.1439	0.3619 ***
ln(K/L)	10.0173	9.3996	0.6177 ***
ln(M/L)	11.1924	10.5557	0.6367 ***
Large (L ≥250)	0.3944	0.1632	0.2312 ***
Medium (50≤L<250)	0.4047	0.2864	0.1183 ***
Small (L<50)	0.2009	0.5504	-0.3495 ***
PC (%)	0.5051	0.3896	0.1155 ***
PC with internet (%)	0.427	0.3233	0.1037 ***
Internet speed	0.1441	0.0832	0.0609 ***
ln(wage)	9.7378	9.444	0.2938 ***
Pay above mean	0.3367	0.1776	0.1591 ***
Males (%)	0.6504	0.6148	0.0356 **
Unpaid workers (%)	0.0018	0.0037	-0.0019
R&D workers (%)	0.011	0.0053	0.0057 **
Exit (=1)	0.0018	0.0016	0.0002
Services	0.5295	0.4832	0.0463 *
Export to sales ratio	0.2675	0.1779	0.0896 ***
Import to sales ratio	0.2074	0.1158	0.0916 ***
HHI	0.1037	0.0776	0.0261 ***
North	0.3372	0.3904	-0.0532 **
Algarve	0.015	0.0336	-0.0186 **
Centre	0.2106	0.2304	-0.0198
Lisbon	0.3582	0.2544	0.1038 ***
Alentejo	0.0353	0.0496	-0.0143
Islands	0.0438	0.0416	0.0022
# firms	1512	487	1610
# observations	3998	625	4623

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

Figure 1. Distribution of firm labour productivity across firms

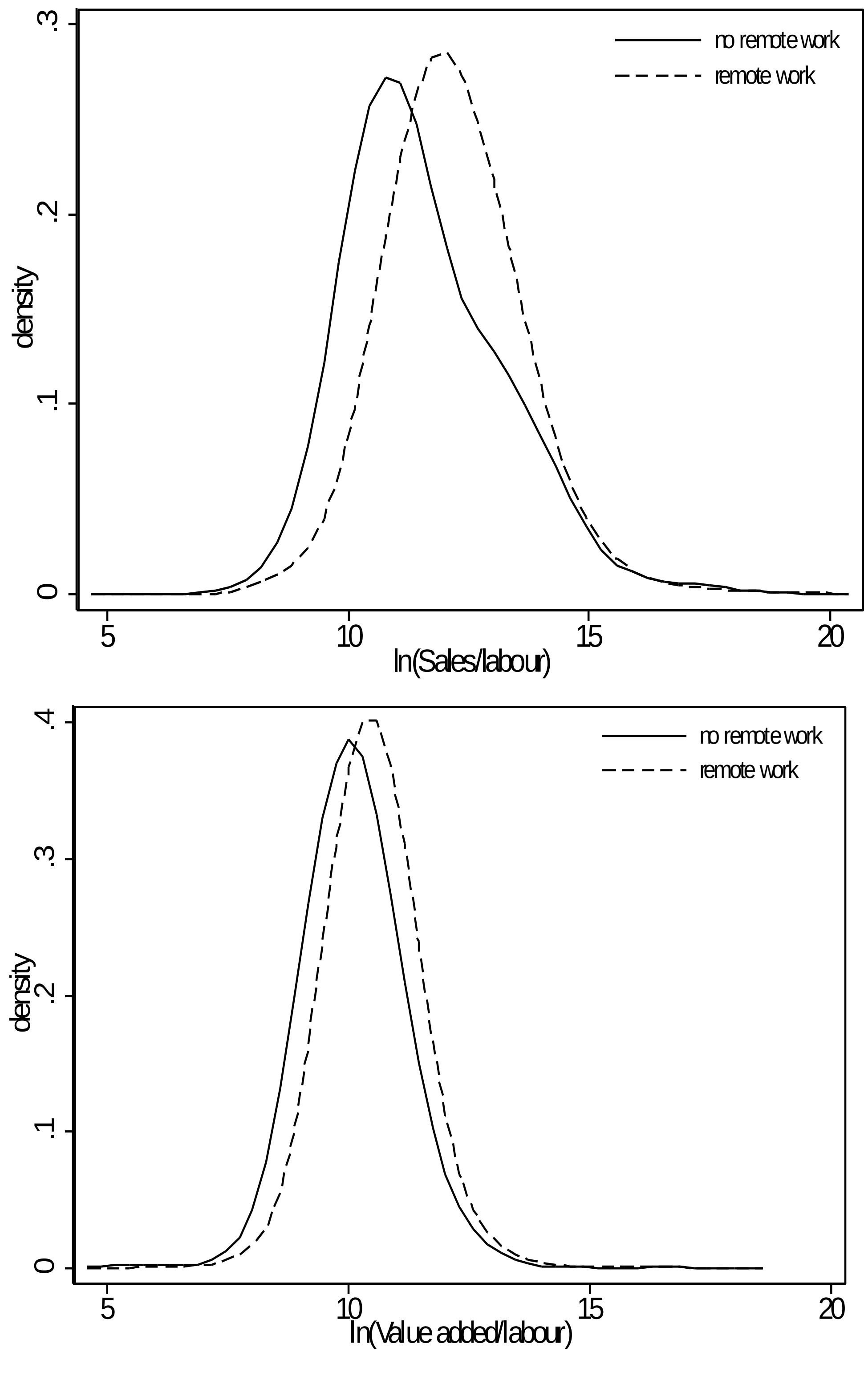

Table 2 - Effects of remote work on labour productivity [ln(Y/L)]

	(1) OLS	(2) OLS	(3) OLS	(4) WITHIN	(5)WITHIN
Remote work	0.1521***	0.1353***	0.0539	-0.0231*	-0.0229*
	(0.0361)	(0.0358)	(0.0330)	(0.0137)	(0.0136)
ln(K/L)	0.0503***	0.0450***	0.0217	0.0017	-0.0001
	(0.0128)	(0.0126)	(0.0136)	(0.0210)	(0.0208)
ln(M/L)	0.5356***	0.5307***	0.4802***	0.3744***	0.3662***
	(0.0178)	(0.0184)	(0.0231)	(0.0394)	(0.0392)
ln(L)	-0.0434***	-0.0453***	-0.0190	-0.2282***	-0.2397***
	(0.0119)	(0.0120)	(0.0195)	(0.0567)	(0.0572)
Part-time (%)		-0.1339	0.3615**	-0.0167	-0.0253
		(0.1242)	(0.1514)	(0.0778)	(0.0758)
Training costs per worker		2.9784***	0.9212*	-0.2323	-0.2616
		(0.5921)	(0.5125)	(0.3248)	(0.3171)
Social expenses per worker		0.4387**	-0.1818	0.3750***	0.3786***
		(0.1732)	(0.1627)	(0.1136)	(0.1181)
Medium			0.0847**	-0.0257	-0.0282
			(0.0343)	(0.0280)	(0.0280)
Small			0.1471**	-0.0678	-0.0796
			(0.0661)	(0.0676)	(0.0673)
PC (%)			-0.0491	-0.0497	-0.0394
			(0.0626)	(0.0434)	(0.0425)
PC with internet (%)			0.2398**	0.1036**	0.0973**
			(0.0955)	(0.0467)	(0.0449)
Internet speed			0.0223	-0.0219	-0.0195
			(0.0304)	(0.0148)	(0.0148)
ln(wage)			0.5167***	0.1165	0.1139
			(0.1889)	(0.0751)	(0.0721)
Pay above mean			0.0752	0.0013	0.0044
			(0.0662)	(0.0144)	(0.0141)
Males (%)			-0.0833	0.1516	0.1302
			(0.0785)	(0.1021)	(0.1014)
Unpaid workers (%)			0.5371	-0.5322	-0.5261
			(0.5481)	(0.4459)	(0.4465)
R&D workers (%)			-0.2618	0.0188	0.0064
			(0.2336)	(0.3501)	(0.3455)
Exit			-0.2866***	-0.1799	-0.1876*
			(0.0954)	(0.1093)	(0.1122)
Export to sales ratio			0.0642	0.1251**	0.1267**
			(0.0502)	(0.0579)	(0.0579)
Import to sales ratio			-0.1350**	-0.0996	-0.0807
			(0.0619)	(0.0781)	(0.0764)
HHI			0.4780***	0.1225	0.0971
			(0.1033)	(0.2022)	(0.2031)
Industry, region and year FE	yes	yes	yes	yes	yes
Firm FE	no	no	no	yes	yes
Industry trends	no	no	no	no	yes
# firms	1610	1610	1610	1610	1610
# observations	4623	4623	4623	4623	4623
Residual sum of squares	1571	1544	1279	106	103

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

Table 3 - Effects of remote work on labour productivity [ln(Y/L)]: RW measurement and sampling weights

	Unweighted		Weighted	
	(1)	(2)	(3)	(4)
Remote work	-0.0229*		-0.0551**	
	(0.0136)		(0.0229)	
Remote work (continuous)		-0.0657**		-0.0997**
		(0.0297)		(0.0483)
Other controls	yes	yes	yes	yes
Industry, region and year FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Industry trends	yes	yes	yes	yes
# firms	1610	1610	1610	1610
# observations	4623	4623	4623	4623
Residual sum of squares	103	103	92	92

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

Table 4 - Effects of remote work on labour productivity [ln(Y/L)]: controlling for managerial quality

	(1)	(2)	(3)	(4)	(5)	(6)
Remote work	-0.0312**		-0.0312**		-0.0288**	
	(0.0157)		(0.0157)		(0.0144)	
Remote work (continuous)		-0.0872**		-0.0873**		-0.0745**
		(0.0357)		(0.0357)		(0.0323)
ln CEO compensation per worker			0.0040	0.0042		
			(0.0125)	(0.0125)		
ln CEO compensation to sales ratio					-0.1327***	-0.1322***
					(0.0230)	(0.0229)
Other controls	yes	yes	yes	yes	yes	yes
Industry, region and year FE	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes
Industry trends	yes	yes	yes	yes	yes	yes
# firms	1175	1175	1175	1175	1175	1175
# observations	3056	3056	3056	3056	3056	3056
Residual sum of squares	57	57	57	57	50	50

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

Table 5 - Effects of remote work on alternative productivity measures

	ln(Value added per worker)		Operational profits	
	(1)	(2)	(3)	(4)
Remote work	-0.0052		-0.0855	
	(0.0213)		(0.3824)	
Remote work (continuous)		-0.0488		-0.2889
		(0.0441)		(0.5886)
Other controls	yes	yes	yes	yes
Industry, region and year FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Industry trends	yes	yes	yes	yes
# firms	1610	1610	1610	1610
# observations	4623	4623	4623	4623
Residual sum of squares	302	302	208431	208428

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

Table 6 - Effects of remote work on labour productivity across firm size

	Small firms (L<50)		Medium (50≤L<250)		Large firms (L≥250)	
	(1)	(2)	(3)	(4)	(3)	(4)
Panel A: ln(Output per worker)						
Remote work	-0.0863***		0.0371**		-0.0063	
	(0.0270)		(0.0155)		(0.0164)	
Remote work (continuous)		-0.1552***		0.0717***		-0.0009
		(0.0511)		(0.0258)		(0.0390)
Other controls	yes	yes	yes	yes	yes	yes
Industry, region and year FE	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes
Industry trends	yes	yes	yes	yes	yes	yes
# firms	526	526	712	712	553	553
# observations	1147	1147	1797	1797	1679	1679
Residual sum of squares	41	41	16	16	17	17
Panel B: ln(Value added per worker)						
Remote work	-0.0955**		0.0786**		0.0150	
	(0.0462)		(0.0309)		(0.0302)	
Remote work (continuous)		-0.1637**		0.1057		0.0031
		(0.0743)		(0.0662)		(0.0817)
Other controls	yes	yes	yes	yes	yes	yes
Industry, region and year FE	yes	yes	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes	yes	yes
Industry trends	yes	yes	yes	yes	yes	yes
# firms	526	526	712	712	553	553
# observations	1147	1147	1797	1797	1679	1679
Residual sum of squares	111	111	84	85	58	58

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

Table 7 - Effects of remote work on labour productivity across industries

	ln(Output per worker)		ln(Value added per worker)	
Remote work	Indicator	Continuous	Indicator	Continuous
	(1)	(2)	(3)	(4)
Remote work*Manufacturing	-0.0138	-0.0522	0.0073	-0.057
	(0.0192)	(0.0459)	(0.0267)	(0.0589)
Remote work*Services	-0.0321*	-0.0650*	-0.0132	-0.0244
	(0.0189)	(0.0351)	(0.0322)	(0.0543)
p -value for equality	0.489	0.811	0.618	0.649
Other controls	yes	yes	yes	yes
Industry, region and year FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Industry trends	yes	yes	yes	yes
# firms	1610	1610	1610	1610
# observations	4623	4623	4623	4623
Residual sum of squares	106	106	310	310

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

Table 8 - Effects of remote work on labour productivity for exporters and non-exporters

	Exporters		Non-exporters	
Remote work	Indicator	Continuous	Indicator	Continuous
	(1)	(2)	(3)	(4)
Panel A: ln(Output per worker)				
Remote work	0.0129	0.0256	-0.1020***	-0.2490***
	(0.0126)	(0.0233)	(0.0303)	(0.0656)
Other controls	yes	yes	yes	yes
Industry, region and year FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Industry trends	yes	yes	yes	yes
# firms	1,175	1,175	640	640
# observations	3,231	3,231	1,392	1,392
Residual sum of squares	43	43	41	41
Panel B: ln(Value-added per worker)				
Remote work	0.0246	0.0217	-0.0867*	-0.2388***
	(0.0247)	(0.0540)	(0.0456)	(0.0892)
Other controls	yes	yes	yes	yes
Industry, region and year FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Industry trends	yes	yes	yes	yes
# firms	1,175	1,175	640	640
# observations	3,231	3,231	1,392	1,392
Residual sum of squares	182	182	84	83

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

Table 9 - Effects of remote work on labour productivity across firms with different skill level

	Low skill		High skill	
Remote work	Indicator	Continuous	Indicator	Continuous
	(1)	(2)	(3)	(4)
Panel A: ln(Output per worker)				
Remote work	-0.0310*	-0.1005**	0.0160	0.0238
	(0.0173)	(0.0464)	(0.0236)	(0.0365)
Other controls	yes	yes	yes	yes
Industry, region and year FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Industry trends	yes	yes	yes	yes
# firms	1452	1452	725	725
# observations	3166	3166	1457	1457
Residual sum of squares	59	59	12	12
Panel B: ln(Value added per worker)				
Remote work	-0.0127	-0.0747	0.0125	-0.0065
	(0.0263)	(0.0695)	(0.0494)	(0.0842)
Other controls	yes	yes	yes	yes
Industry, region and year FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Industry trends	yes	yes	yes	yes
# firms	1452	1452	725	725
# observations	3166	3166	1457	1457
Residual sum of squares	152.9	152.8	49.52	49.52

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

Table 10 - Effects of remote work on labour productivity for firms with and without R&D activities

R&D activities	No		Yes	
Remote work	Indicator	Continuous	Indicator	Continuous
	(1)	(2)	(3)	(4)
Panel A: Output per worker				
Remote work	-0.0266*	-0.0785**	0.0367**	0.0925**
	(0.0147)	(0.0319)	(0.0175)	(0.0403)
Other controls	yes	yes	yes	yes
Industry, region and year FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Industry trends	yes	yes	yes	yes
# firms	3,882	3,882	741	741
# observations	1,454	1,454	307	307
Residual sum of squares	91	91	2	2
Panel B: Value added per worker				
Remote work	-0.0025	-0.0526	0.0604	0.0369
	(0.0235)	(0.0478)	(0.0439)	(0.0826)
Other controls	yes	yes	yes	yes
Industry, region and year FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Industry trends	yes	yes	yes	yes
# firms	3,882	3,882	741	741
# observations	1,454	1,454	307	307
Residual sum of squares	250.8	250.7	24.89	24.94

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

Table 11 - Effects of remote work on labour productivity for adopters versus abandoners

	ln(Output per worker)		ln(Value added per worker)	
Remote work	Indicator	Continuous	Indicator	Continuous
	(1)	(2)	(3)	(4)
Remote work*adoption	-0.0300*	-0.0786**	-0.0528*	-0.1293**
	(0.0160)	(0.0312)	(0.0276)	(0.0514)
Remote work*abandonment	-0.0127	-0.0735	0.0627	0.0521
	(0.0254)	(0.0631)	(0.0390)	(0.0746)
p -value for equality	0.576	0.944	0.023	0.050
Other controls	yes	yes	yes	yes
Industry, region and year FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Industry trends	yes	yes	yes	yes
# firms	1610	1610	1610	1610
# observations	4623	4623	4623	4623
Residual sum of squares	102.9	102.7	301.8	301.7

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

Table 12 - Propensity score estimates (Probit)

Sample		
Treated firms	adopt RW	abandon RW
Control firms	never adopt RW	permanent use RW
Ln(Y)	0.0790	-0.2485***
	(0.0906)	(0.0493)
Ln(Y/L)	-0.0393	0.0579
	(0.1238)	(0.0621)
ln(K)	0.1433**	-0.0598*
	(0.0586)	(0.0353)
ln(wage)	0.4605*	-0.2725**
	(0.2799)	(0.1283)
Sales growth rate	-0.0273	-0.3354***
	(0.1046)	(0.1120)
Capital per employee growth rate	0.1126**	-0.001
	(0.0472)	(0.0021)
Industry, region and year FE	yes	yes
# firms	327	1278
# observations	341	2344
Pseudo R square	0.3000	0.3198
% observations correctly predicted	77.13%	93.69%

Notes: All independent variables in levels are lagged one year prior to adoption/abandonment of RW. Growth of sales and capital/labour ratio is computed between the year prior to adoption (abandonment) of RW and the adoption (abandonment) of RW year. Significance level at which the null hypothesis is rejected: ***, 1%; **, 5%; and *, 10%. The standard errors in parentheses are clustered at firm-level.

Table 13 - Effects of remote work on labour productivity for adopters vs abandoners - matched sample

	ln(Output per worker)		ln(Value added per worker)	
Remote work	Indicator	Continuous	Indicator	Continuous
	(1)	(2)	(3)	(4)
Remote work*adoption	-0.0712**	-0.1409**	-0.1346**	-0.1876
	(0.0326)	(0.0577)	(0.0669)	(0.1137)
Remote work*abandonment	0.0295	0.0428	0.1140**	0.1653*
	(0.0254)	(0.0421)	(0.0499)	(0.0926)
p -value for equality	0.0273	0.0112	0.0066	0.0236
Other controls	yes	yes	yes	yes
Industry, region and year FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Industry trends	yes	yes	yes	yes
# firms	250	250	250	250
# observations	696	696	696	696
Residual sum of squares	8.163	8.12	24.55	24.72

Notes: Significance level at which the null hypothesis is rejected: ***, 1%; **, 5%; and *, 10%. The standard errors are clustered at firm level. The number of matched firms that adopted (abandoned) remote work (RW) is 35 (105). Firms that adopt RW are matched with firms that never adopt RW, while firms that abandon RM are matched with firms that always use RW. Treated firms are matched in the first year they appear in the data by sales, labour productivity, capital, wage, growth of sales and capital/labour ratio. We also impose exact matching by industry, year, size and region. We use the nearest neighbour imposing the caliper of 0.1 and common support.

Table 14 - Effects of remote work on labour productivity [ln(Y/L)] across skill levels, R&D activities and firm size

Skill level	Low		High	
Remote work	Indicator	Continuous	Indicator	Continuous
	(1)	(2)	(3)	(4)
Remote work*Small	-0.0949***	-0.1854***	0.0473	0.0076
	(0.0321)	(0.0678)	(0.0526)	(0.0652)
Remote work*Medium	0.0281	0.0245	0.0023	0.0143
	(0.0188)	(0.0496)	(0.0334)	(0.0504)
Remote work*Large	0.0033	0.0612	-0.0002	0.0747
	(0.0223)	(0.0602)	(0.0383)	(0.0657)
p -value for equality	0.0034	0.0193	0.7362	0.6869
Other controls	yes	yes	yes	yes
Industry, region and year FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Industry trends	yes	yes	yes	yes
# firms	1452	1452	725	725
# observations	3166	3166	1457	1457
Residual sum of squares	59	58	12	12
R&D activities	No		Yes	
Remote work	Indicator	Continuous	Indicator	Continuous
Remote work*Small	-0.0777***	-0.1404***	0.0664	0.1990***
	(0.0259)	(0.0443)	(0.0470)	(0.0752)
Remote work*Medium	0.0248	0.0006	0.1466***	0.1103
	(0.0173)	(0.0387)	(0.0489)	(0.0718)
Remote work*Large	-0.0006	0.0746	0.0068	0.0734*
	(0.0214)	(0.0551)	(0.0161)	(0.0386)
p -value for equality	0.0035	0.0071	0.0225	0.233
Other controls	yes	yes	yes	yes
Industry, region and year FE	yes	yes	yes	yes
Firm FE	yes	yes	yes	yes
Industry trends	yes	yes	yes	yes
# firms	3,882	3,882	741	741
# observations	1,454	1,454	307	307
Residual sum of squares	90.46	90.11	2	2

Notes: Significance level at which the null hypothesis 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 work	Indicator variable if the firm adopts RW	IUTIC
Remote work (%)	Share of employees that can work remotely in a 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 output 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
Profits	Operational profits (prices =2016)	SCIE
Other firm variables		
PC (%)	Share of workers that use PC at least once per week	IUTIC
PC with internet (%)	Share of workers that use PC with internet access per week	IUTIC
Internet speed	Indicator variable for high internet speed	IUTIC
Portable computer	Indicator variable if the firm has given portable computer with internet access to employees	IUTIC
Portable computer (%)	Share of employees that use portable computer with internet access at work	IUTIC
Export to sales ratio	Exports to sales ratio	SCIE
Import to sales ratio	Imports to sales ratio	SCIE
Ln(wage)	Log of average real wage (prices =2016)	SCIE
Pay above	Indicator variable if the firm pays on average above the mean industry level (21 industries were mildly defined at 2 digit level)	SCIE
Males (%)	Share of male employees	SCIE
Unpaid workers (%)	Share of unpaid employees	SCIE
R&D workers (%)	Share of employees involved in R&D activities	SCIE
Exit	Indicator variable if the firm leaves the market	SCIE
Large	Indicator variable if the firm has at least 250 employees	
Medium	Indicator variable if the firm has at least 50 and less than 250 employees.	
Small	Indicator variable if the firm has at less than 50 employees	
Location	6 regions defined at NUTS2 level	SCIE
Industry	21 industries were mildly defined at 2 digit level	SCIE
HHI	Herfindahl-Hirschman sales index defined at 5 digit level of economic activity	SCIE

Table A2. Differences in variable means, matched sample, year prior to treatment (adoption of RW)

Variables	Treated firms: adopt RW	Control firms: never adopt RW	Difference in means, t-test	p-value
Ln(Y)	15.497	15.231	0.44	0.660
Ln(Y/L)	12.361	11.902	1.19	0.237
ln(K)	13.295	12.704	1.25	0.215
Ln(wage)	9.485	9.3879	0.81	0.423
Sales growth rate	0.121	0.171	-0.21	0.831
Capital per employee growth rat	0.005	0.200	-0.94	0.348
Medium	0.400	0.400	0	1
Small	0.600	0.600	0	1
Food, beverages	0.086	0.086	0	1
Textiles, clothing, leather	0.086	0.086	0	1
Minerals, metallic products	0.029	0.029	0	1
Equipment	0.086	0.086	0	1
Other	0.057	0.057	0	1
Transport equipment	0.029	0.029	0	1
Wholesale trade	0.400	0.400	0	1
Retail trade	0.057	0.057	0	1
Hotels , restaurants	0.143	0.143	0	1
Other services	0.029	0.029	0	1
			0	1
North	0.486	0.486	0	1
Centre	0.086	0.086	0	1
Lisbon	0.400	0.400	0	1
Alentejo	0.029	0.029	0	1
2012	0.457	0.457	0	1
2013	0.171	0.171	0	1
2016	0.371	0.371	0	1

Table A3. Differences in variable means, matched sample, year prior to treatment (abandonment of RW)

Variables	Treated firms: adopt RW	Control firms: never adopt RW	Difference in means, t-test	p-value
Ln(Y)	15.887	15.937	-0.17	0.866
Ln(Y/L)	11.744	11.726	0.08	0.940
ln(K)	13.489	13.638	-0.44	0.663
Ln(wage)	9.488	9.543	-0.72	0.471
Sales growth rate	0.061	0.085	-0.43	0.664
Capital per employee growth rate	0.949	0.260	1.03	0.306
Medium	0.248	0.248	0	1
Small	0.467	0.467	0	1
Food, beverages	0.038	0.038	0	1
Textiles, clothing, leather	0.095	0.095	0	1
Chemicals, pharmaceuticals, rubber	0.010	0.010	0	1
Minerals, metallic products	0.038	0.038	0	1
Equipment	0.143	0.143	0	1
Other manufacturing	0.019	0.019	0	1
Transport equipment	0.124	0.124	0	1
Electricity, water, waste	0.029	0.029	0	1
Construction	0.019	0.019	0	1
Car repair	0.038	0.038	0	1
Wholesale trade	0.162	0.162	0	1
Retail trade	0.010	0.010	0	1
Transportation, storage	0.038	0.038	0	1
Hotels , restaurants	0.095	0.095	0	1
Cinema, radio, TV	0.010	0.010	0	1
Telecommunications	0.010	0.010	0	1
Other services	0.124	0.124	0	1
North	0.400	0.400	0	1
Algarve	0.019	0.019	0	1
Centre	0.162	0.162	0	1
Lisbon	0.390	0.390	0	1
Alentejo	0.010	0.010	0	1
Islands	0.019	0.019	0	1
2012	0.028	0.028	0	1
2013	0.103	0.103	0	1
2016	0.869	0.869	0	1

Table A4. Quality of the matching procedure

Sample		Pseudo R2	Chi-square	P-value	Mean Bias	Median Bias
Adoption of RW	Unmatched	0.300	130	0.000	27.7	13.2
	Matched	0.171	17	0.551	4.2	0.0
Abandonment of RW	Unmatched	0.320	373	0.000	29.0	15.8
	Matched	0.014	4	1.000	1.2	0.0