Remote work and incentives before and after the pandemic

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Abstract

We propose a firm-worker model to explain two facts: the post-pandemic persistence of remote work and the rise in the use of performance pay. Pre-pandemic, the firm incentivizes workers at business premises through fixed salary with effort monitoring or variable performance-based pay. As workers' productivity increases, the required performance premium required falls. Hence, given workers' risk aversion, firms save by using performance pay if productivity is high enough and prefer fixed pay otherwise. The pandemic, modeled as an unforeseen shock, forces the firm to adopt remote work, making monitoring less effective and increasing the firm's use of performance pay. Post-pandemic, the firm adopts remote work for workers who prefer it and are productive enough to be paid on performance. Low-productivity workers return to business premises if monitoring is ineffective. The model predicts reduced remote work for low-productivity workers due to decreased efficacy of remote monitoring. Based on the conjecture that regulation affects the efficacy of remote monitoring, we exploit the heterogeneity in the state legislation within the US to test the effect of such restrictive regulation on the share of remote work days by estimating the long-run correlation via OLS and identifying the causality with a Diff-in-Diff approach. The evidence strongly supports the prediction. Our analysis suggests that pandemic health policies and regulations might affect remote work and performance pay diffusion.

Keywords: Remote Work, Performance Pay, Monitoring, Productivity.

JEL codes: J24, J33, M52, L23.

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1 Introduction

The pandemic triggered an unprecedented surge in remote work. In the US, as documented in a systematic way by Barrero et al. (2021), the incidence of remote working days increased from 7.2% in 2019 to a spectacular 61.51% in 2020. Certainly, some of that change reverted as the temporary pandemic-related restrictions were lifted. Yet, as reported by the same authors, the incidence of remote work still stands at 27.5% as of March 2024, which suggests that the pandemic triggered a structural change in the relevance of remote work. Aksoy et al. (2022), and lately Zarate et al. (2024), shows that such a structural change is positively associated with the stringency of pandemic health policies.

Along with remote work, there is evidence that performance pay has become an increasingly popular incentive scheme during and after the pandemic. A preliminary study that the authors request to not cite reports that remote job vacancies are twice as likely to pay according to performance compared to office jobs. Such evidence suggests that remote work and performance pay complement each other.

Our paper aims to explain such evidence based on a theoretical mechanism supported by the data. We develop a tractable model of the relationship between a firm and a worker that rationalizes the observed increased use of remote work and performance pay during the pandemic and their persistence afterward, which so far has been especially pronounced in regions where lockdown policies were longer and more stringent. The model delivers a testable implication uniquely tied to our proposed mechanism, for which we find robust evidence, as reviewed below. The firm, which lives for three periods, needs a worker's labor to produce. The expected output of the production process depends on the level of effort exerted by the worker, which is non-contractible. The firm chooses whether to incentivize the worker through a fixed salary with effort monitoring or performance pay. Moreover, the firm can either adopt a business model such that the worker works at business premises or one in which the worker works remotely. The three periods cover the pre-pandemic, pandemic, and post-pandemic phases, where the pandemic is modeled as an unforeseeable event with zero probability.

The core mechanism underlying the model's results hinges on four realistic assumptions. First, workers are risk-averse[1]. Second, ceteris paribus, they prefer remote work to office work.[2] Third, monitoring the worker's effort is less effective under remote work than under office work, which is intuitively a valid assumption to the extent that there are ways of monitoring workers' efforts that are unavailable if the worker works remotely, while the reverse is, in principle, not true. Fourth, before the pandemic, the firm adopted the office business model, which was regarded as more efficient than the remote one. This assumption follows from the evidence discussed at the beginning of the introduction, indicating that remote work was not very common prior to the pandemic.

The main model's results are as follows. In the pre-pandemic phase, when the worker works at business premises, the firm uses performance pay to incentivize the worker only if the worker's productivity is sufficiently high. Otherwise, fixed pay with worker's effort monitoring applies. Such a relationship between the worker's productivity and the incentive scheme adopted by the firm is consistent with the evidence provided by Eriksson and Villeval (2008), and Ewing (1996). The result follows from the fact that the expected cost of the performance pay scheme, in terms of wages, decreases with the productivity of the worker. If a worker is more productive, the incentive-compatible performance premium falls because a more productive worker is more likely to earn the premium by exerting effort than a less productive one. A lower performance premium means less variability in pay, which constitutes valuable insurance for the risk-averse worker. As a result, under performance pay, a more productive worker is willing to accept a lower expected salary than a less productive one. That explains why the firm uses performance pay if the worker productivity is sufficiently high and fixed pay with monitoring otherwise.

The pandemic shock forces the firm to adopt remote work if viable. The productivity threshold below which a worker is paid with fixed wage is reduced - and performance pay becomes relatively preferable because monitoring workers' efforts under remote work is less effective than under office work. Post-pandemic, having incurred the related infrastructural costs, the firm would, in principle,

[1]For a comprehensive theoretical and empirical discussion that corroborates this assumption, see Chetty (2006) and Cohen and Einav (2007).

[2]As discussed by Bick et al. (2023), there is substantial recent literature based on experimental and micro-data that documents workers' significant willingness to pay to have the possibility to work from home. See Mas and Pallais (2017), Maestas et al. (2023), Barrero et al. (2021).

tend to stick to remote work as workers prefer it. However, this is only optimal if the worker's productivity is high enough that performance pay is the convenient incentive scheme for the firm or if the efficacy of effort monitoring under remote work is sufficiently effective to incentivize less productive workers on a fixed salary. Otherwise, for low-productivity workers paid a fixed salary, the firm would switch back to office work where monitoring is more effective.

One of the key insights of the model is that the persistence of remote work post-pandemic is triggered by the pandemic shock that forces the firm to adopt the business model based on remote work. This theoretical result is consistent with the evidence that the diffusion of remote work increases with the stringency of government-mandated policies aimed at containing the spread of the pandemic, such as lockdown policies (Aksoy et al., 2022; Zarate et al., 2024). In states where stringent pandemic health policies were implemented, the surge of remote work shows significant persistence after the pandemic. That has not been the case in areas in which such health policies were not implemented, which implied that firms were not forced to adopt remote work.

Crucially, the model delivers a testable implication that follows directly from the different effectiveness of monitoring under remote and office work, which allows us to test whether the key mechanism we propose is empirically relevant. Specifically, our model predicts that post-pandemic, as the effectiveness of firms' monitoring of workers' effort under remote work falls, we should observe less remote work by workers whose productivity is sufficiently low. Based on the conjecture that restrictive regulation reduces the efficacy of remote effort monitoring, we exploit the heterogeneity in the state legislation within the US to test the effect of such restrictive regulation on the share of remote work days based on a pooled OLS and a Difference-in-Differrence (Diff-in-Diff) approach using data from the Survey of Working Arrangements and Attitudes (SWAA), (see Barrero et al. (2021)). We find strong empirical support for our prediction. With the OLS, we first document a robust correlation between the existence of regulations of firms' monitoring activities and remote work for low-skill, and therefore less productive, workers across US' states. Then, through a triple Diff-in-Diff, we exploit the introduction of a more severe regulation in the state of New York during the pandemic to identify causality. We find a significant and negative effect of the restrictive regulation on remote work days by low-skill workers within the state, which is robust under alternative specifications. In other words, the introduction of the legislation caused a reduction of about 4% days of remote work relative to total working days for low-skill workers within the state.

Notably, our theoretical and empirical analysis offer indirect support the idea that remote monitoring technologies employed by firms, by effectively mitigating the asymmetric information problems typical of any firm-worker relationship, played a crucial role in the escalation of remote work. In the absence of direct data on the usage of such monitoring technologies, the evidence that we provide negative impact induced on the adoption of remote work by the introduction of restrictive regulations on electronic monitoring can be interpreted as indirect evidence of the relevance of remote monitoring. In turn, such relevance of remote monitoring suggests the importance of overcoming the potential moral hazard problem caused by the asymmetry of information between the firm and the worker, whereby only the worker observes her effort. Finally, the significant impact of these regulations on firms' strategies regarding the business model and the incentive schemes suggests that they can have a significant aggregate impact on remote work, partly explaining the cross-regional differences documented in the literature (Aksoy et al., 2022; Zarate et al., 2024).

The paper contributes to three strands of literature. First, by providing a tractable model of the firm's choice between performance pay and fixed pay with monitoring as alternative incentive schemes for the worker, we add to the significant existing research on the provision of incentives within the firm. Bénabou and Tirole (2016), uncover the link between competition across firms and the adoption of performance pay, while Lazear (2000), shows that performance pay affects productivity. Bandiera et al. (2009), provide experimental evidence on the interplay between the provision of managerial incentives and earnings inequality among lower-tier workers. More closely related to our work, Lemieux et al. (2009) shows that compensation in performance-pay jobs is more closely related to observed and unobserved productive characteristics of workers than compensation in non-performance-pay jobs, and relate this finding to the possibility that performance pay might be one of the drivers of wage inequality under skill-biased technological progress. Their theoretical mechanism is different from ours since we emphasize the role of workers' risk aversion in determining the effect of workers' productivity and remote work on firms' adoption of performance-pay schemes. Also related to our work, Bandiera et al. (2015), show that more risk-averse and less talented managers demand low-powered incentive schemes. Complementary to that, we show that more productive workers can be incentivized with less extreme performance premia, which is less costly to the extent that workers are risk averse. Finally, Dohmen and Falk (2011) shows that, in a lab experiment, the output is higher in the variable-payment schemes compared to the fixed-payment scheme, due largely to productivity sorting. Such a finding also suggests a link between performance pay and workers' productivity.[3]

Second, our analysis adds to the literature on the evolution trend of remote work. Barrero et al. (2021), provide a model to explain why remote work was not widely adopted prior to the pandemic and why it is likely to be persistent post-pandemic. The mechanism they propose, which relates to ours, is based on the imperfect knowledge that firms had about such a model until the pandemic forced them to implement it. They also provide extensive evidence about the surge of remote work and the determinants of its persistence, including investments in physical, human, and organizational capital. Also Bick et al. (2023) document the increase and the persistence of work-from-home, and they provide evidence that the benefits to workers and employers due to the adoption of work-from-home explain the persistence of work-from-home after the pandemic. Dingel and Neiman (2020), study the feasibility of remote work across jobs. Related to that, Mateyka et al. (2012) provides information about the characteristics of home-based workers in 2010. Gaspar and Glaeser (1998), investigate the impact of information technology on remote work, while Oettinger (2011), focuses on the wage consequences of working from home.

Finally, the paper adds to the debate on the effects of the pandemic on the labor market. Aside from Barrero et al. (2021), and Bick et al. (2023), which we already discussed above, other relevant contributions include Brynjolfsson et al. (2020), who documents the impact of Covid-19 on remote work, Adams-Prassl et al. (2020), and, Foote et al. (2020).

The rest of the paper is structured as follows. Section 2 presents the model. Section 3 derives the optimal incentive schemes. Section 4 characterizes the behavior of the firm before, during, and after the pandemic, deriving the main results and the related empirical predictions. 5 discusses the empirical evidence and section 6 concludes.

[3]The link between sorting and performance pay has also been investigated by Eriksson and Villeval (2008).

2 The model

We consider a three-period economy populated by one risk-neutral firm living for three periods and a sequence of three one-period living identical workers, with only one worker present in each of the three periods. In each $t = 0, 1, 2$, the firm operates a production process that requires one unit of worker's labor and delivers an output,

$$Y = \begin{cases} Y_H > 0 & \text{with probability } p_e \\ 0 & \text{with probability } 1 - p_e \end{cases} \tag{1}$$

at the end of the period. The probability of success, p_e, depends positively on the level of effort, e, exerted by the worker, where $e \in \{e_L, e_H\}$. Accordingly, the output of the production process depends on the worker's effort.

The firm organizes production by choosing between two alternative business models, O and R, which stand for "office" and "remote," respectively. Under model O, the worker contributes to the production process at the business premises, while under model R, the worker contributes to the production process remotely.

The implementation the business model $i = O, R$ requires a one-time fixed investment costing C_i. We assume no depreciation over the three periods. C_i has a broad interpretation. It comprises costs related to material and immaterial infrastructures, such as buildings, office supplies, software and equipment, human resources, and organizational developments. Importantly, it also includes the costs of uncertainty about the effectiveness of the business model and cultural costs as well. The cost of uncertainty relates to how common or well-established the business model is. This cost can be significantly higher for innovative or unprecedented models because of the lack of widely available knowledge due to the limited adoption. The culture cost depends on how typical or traditional a business model is given the prevailing business culture. Clearly, also this cost can be significantly higher for new models.

Based on the above discussion, given the robust evidence that pre-pandemic, remote work was not very common, we assume that, at time $t = 0$, before the pandemic shock, $C_O < C_R$ holds in such a way that, as discussed later on in the paper, in the absence of a pandemic, the firm prefers to implement the O model rather than the R one. Indeed, the fact that before the pandemic, the O model was widely used while the adoption of the R model was limited suggests that the firm faces substantially more uncertainty about the viability and efficacy of the R model compared to the O one.[4] The implicit view is that prior to the pandemic, the investments in human resources, software, and equipment required by the R business model, coupled with the uncertainty about its feasibility and effectiveness and cultural costs, significant enough to make the O model the widely adopted model. In other words, the fact that up to the pandemic the O model was the one mostly adopted implies that it was the most effective one. We model this through a difference in the setup costs of the two models. [5]

Each of the workers interacting with the firm is identical to the others. The representative worker is risk-averse with utility

$$u(c, e) = \alpha_i c^a - e^b \tag{2}$$

where c is consumption, $e \in e_L, e_H$ is effort; $a \in (0, 1)$ and $b > 0$ are two parameters measuring the elasticity of the utility of consumption and the disutility of effort, respectively, and; α_i is a parameter that makes the utility of consumption depend on whether the worker works remotely($i = R$) or in presence at the office ($i = O$). In other words, we assume that the organizational model chosen by the firm could affect the worker's utility.[6] Specifically, we assume $\alpha_R \geq \alpha_O \equiv 1$ to capture the idea that working remotely yields the worker a higher utility as if the wage earned

[4]Specifically, since the R model was new and not widely adopted before the pandemic, the firm might have incorrect priors about its viability. The firm might be uncertain about whether informational flows between workers and the firm will be smooth enough and, above all, whether the worker's productivity at home will be sufficient. Conversely, the office business model typically involves lower uncertainty regarding these factors, as traditional in-person work environments are more established and predictable.

[5]Typical examples include of costs related to the R model include investments in state-of-the-art ICT at the worker's home and at the business premises and training of the personnel to enhance the usage of teleconferencing software. (Barrero et al., 2021) estimate that these are substantial, amounting to \$2,005 per remote employee, which is equivalent to 0.7% of annual GDP. The authors believe this is a lower bound because the survey does not capture investments made at the business premises and in the cloud.

[6]We could adopt an equivalent formulation in which the utility would be a function of consumption and leisure, where leisure would be defined as negatively related to effort. For instance, we could adopt the following specification

$$u(c, l) = \alpha_i c^a + l \tag{3}$$

with $l = T - e$, where T is a positive constant.

remotely has a higher real value than that earned at the office due to savings in both monetary and non-monetary costs.[7] Note that since the worker lasts one period, she uses all her salary, w, to consume so that in equilibrium, $u = \alpha_i w^a - e^b$ with $\alpha_R^{\frac{1}{a}} > 1$ being the parameter that measures the positive effect on real wages.

Regarding the relationship between the worker and the firm, we assume that the outside option available to the worker yields zero utility, and the firm sets the labor contract.

2.1 Monitoring technologies: effort and performance

Effort is privately observed by the worker so that once the firm hires the worker, an information asymmetry emerges. Since the worker benefits from choosing low effort, such an asymmetry could lead to a moral hazard problem.

The firm has access to two monitoring technologies to reduce the ex-post asymmetric information about the worker's effort. The first one allows the firm to verify the level of effort exerted by the worker, where such monitoring activity is effective with probability θ_i and ineffective otherwise. We assume that the effectiveness of the monitoring, which is measured by θ_i, is specific to the organizational model, i. Our intuition is that monitoring workers' efforts is less effective in the case of remote work compared to work on business premises. Indeed, with remote work, a company cannot monitor workers except by using effective distance-based techniques, i.e. remote monitoring techniques. In other words, remote work renders all the traditional monitoring techniques used at business premises unfeasible. Differently, when workers are on business premises, the company can adopt both conventional and remote monitoring techniques. Accordingly, we assume $\theta_O \geq \theta_R$.[8]

The other technology allows the firm to monitor the early advancement of the production process at an interim date. Specifically, the firm can observe an early signal, s, about the advancement of the production process, which can be either H or L, i.e. $s = \{s_L, s_H\}$, with $s_H > s_L$. We let the probability of the signal s, $\sigma_{s,e}$, depend on the worker's effort, such that the probability of observing

[7]For example, Aksoy et al. (2023) document the savings in commuting time resulting from remote work. They also provide evidence about the allocation of these time savings: a large part, 40 percent, is devoted to primary and secondary jobs, but 34 percent goes to leisure and 11 percent to care-giving activities.

[8]In principle, this framework can be extended by requiring the firm to incur a cost $M_{j,i} > 0$ to monitor workers' effort, $j = F$, or workers' performance, $j = P$. In practice, including monitoring costs do not provide any additional relevant insight. For this reason, we normalize all 4 monitoring costs to zero.

a H (L) signal is higher (lower) when the worker's effort is H (L). Formally, $\sigma_{H,H} > \sigma_{H,L}$, which implies $\sigma_{L,H} < \sigma_{L,L}$, given $\sigma_{L,e} + \sigma_{H,e} = 1$. In other words, the probability of observing a high signal is higher conditional on high effort than low effort. Yet, we assume $\sigma_{H,L} > 0$, which implies that the signal is not perfectly informative about the level of effort exerted by the worker. Based on the signal, s, the conditional probability of success of the firm's project is v_s, with $v_H > v_L$.

Given such a probabilistic structure, the value of the unconditional probability of success of the production process is

$$p_e = \sigma_{H,e}v_H + (1 - \sigma_{H,e})v_L. \tag{4}$$

Note that $\sigma_{H,H} > \sigma_{H,L}$ implies $p_H > p_L$ coherently with our primitive assumption that a worker's effort has a positive effect on the probability of success of the project, p_e. Based on equation (4), the expression of the gross expected product generated by the firm at date 1 is

$$E(Y|e) = [\sigma_{H,e}(v_H - v_L) + v_L]Y, \tag{5}$$

so that the increase in the firm's expected return induced by an increase in the worker's effort is

$$MP_e = \Delta\sigma[v_H - v_L]Y, \tag{6}$$

with $\Delta\sigma \equiv \sigma_{H,H} - \sigma_{H,L}$. Note that MP_e depends both on the characteristics of the production process $[v_H - v_L]Y$ and on $\Delta\sigma$, which represents the impact of the worker's effort on the probability of observing a positive signal about the prospects of production. We interpret $\Delta\sigma$ as a measure of the worker's productivity within the firm. In general, $\Delta\sigma$ depends on workers' ability, skills, and other relevant characteristics, as well as on the importance of the task the worker performs within the firm's production process. For example, $\Delta\sigma$ is relatively high for a worker whose task is to develop an AI tool, which represents the main product of the firm, while it is relatively low if the same worker is one of many operators in a call center of the same firm. Similarly, for a given task, $\Delta\sigma$ can be thought to be relatively higher when the worker is more able or skilled. While we do not model such determinants of worker productivity explicitly, we use them to interpret the evidence aimed at testing the model's predictions. Specifically, we use the intuition that better-educated workers usually perform key tasks or occupations to proxy $\Delta\sigma$ with a measure of educational attainment.

Given the available monitoring technologies, there are two ways in which the firm can provide the worker with the incentive to exert high effort. One possibility is to monitor the worker's effort, pay the worker with a fixed wage schedule, $w_{F,i}$, and fire the worker if the worker is found shirking. We refer to this as the incentive scheme "F". Alternatively, the firm can monitor the early advancement of the project and pay a high wage, $w_{H,i}$, in case of a high signal and a low wage, $w_{L,i}$, in case of low signal. Paying different salaries depending on the observed signal corresponds to a "performance pay scheme" since the worker's effort affects the probability of observing a high signal about the advancement of the project so that high signal constitutes a meaningful signal of the worker's effort. We label "P" such a performance pay scheme.

2.2 Timing and the pandemic shock

In each of the three periods, the timing is as follows:

1. The firm chooses the organizational model and the incentive scheme to pay the worker and makes a take or leave offer to the worker;
2. The worker decides whether to accept or reject;
3. Production takes place, and payoffs are realized and distributed.

At time $t = 1$, a pandemic shock hits the economy that prevents the firm at time $t = 1$ from operating under model O. The pandemic shock is modeled as an unforeseeable event characterized by zero probability, so the firm does not consider it when deciding how to organize production. In other words, the firm does not assign a positive probability to such a shock, ex-ante.[9]. At time $t = 2$, the pandemic event ends, and the economy turns back to normal.[10]

[9]Specifically, at time $t = 0$, the firm does not assign any value to the option of paying the infrastructural cost associated with model R in order to be able to operate at date $t = 1$ in the case of a pandemic shock. That follows from the fact that there are no foreseeable benefit of organizing the firm to deal with such a pandemic shock

[10]Notice that the three-periods setting could be generalized. In particular, the model can be extended to an infinite horizon setting where periods 0 and 2 could last an infinite amount of time.

3 Optimal incentive schemes

Before turning to the equilibrium analysis, we characterize the two alternative optimal incentive schemes the firm could use to incentivize the worker. All the analysis is conditional on the organizational model, $i = O, R$, adopted by the firm.

3.1 Fixed pay scheme with monitoring of the worker's effort

At any time $t = 0, 1, 2$, the fixed wage schedule w_i associated with the fixed pay scheme, F, should satisfy the following incentive compatibility constraint (ICC) and participation constraint (PC):

$$ICC: \quad \alpha_i w_i^a - e_H^b \geq (1 - \theta_i)\alpha_i w_i^a - e_L^b \tag{7}$$

$$PC: \quad \alpha_i w_i^a - e_H^b \geq 0 \tag{8}$$

The ICC says that the expected utility from exerting high effort should exceed the expected utility of shirking. The PC says that the expected utility from participation should exceed the utility associated with the outside option, where the latter equals zero.

It is immediate to verify that the optimal fixed wage schedule satisfies

$$w_i^F = \max\left(\left(\frac{e_H^b - e_L^b}{\alpha_i \theta_i}\right)^{\frac{1}{a}}, \left(\frac{e_H^b}{\alpha_i}\right)^{\frac{1}{a}}\right) \tag{9}$$

Since we are interested in the case in which moral hazard is binding, we assume that the effectiveness of monitoring effort is low enough. Specifically, we make the following

Assumption 1.

$$\theta_i < 1 - \frac{e_L^b}{e_H^b}.$$

so that

$$w_i^F = \left(\frac{e_H^b - e_L^b}{\alpha_i \theta_i}\right)^{\frac{1}{a}} \tag{10}$$

Note that w_i^F is decreasing in the effectiveness of monitoring, θ_i. The higher the effectiveness of monitoring, the more powerful the incentive scheme based on the combination of monitoring and the fixed-wage schedule, which implies that the firm could set a lower wage. Moreover, w_i^F is decreasing in α_i and a: the incentive-compatible fixed wage decreases with the marginal utility of consumption. Finally, w_i^F increases with $(e_H^b - e_L^b)$: the firm needs to pay a higher salary in order to incentivize the worker when her benefits from shirking are higher.

3.2 Performance pay scheme with monitoring of the worker's performance

Under the performance pay scheme, P, the wage schedule takes the form of a lottery, $\omega_i = [w_{H,i} \circ \sigma_{H,H}; w_{L,i} \circ (1-\sigma_{H,H})]$, with an associated "performance premium" measured by $w_{H,i} - w_{L,i}$, which must satisfy the following incentive compatibility (ICC) and participation constraints (PC):

$$ICC \quad : \quad \sigma_{H,H}\alpha_i w_{H,i}^a + \sigma_{L,H}\alpha_i w_{L,i}^a - e_H^b \geq \sigma_{H,L}\alpha_i w_{H,i}^a + \sigma_{L,L}\alpha_i w_{L,i}^a - e_L^b \tag{11}$$

$$PC \quad : \quad \sigma_{H,H}\alpha_i w_{H,i}^a + \sigma_{L,H}\alpha_i w_{L,i}^a - e_H^b \geq 0 \tag{12}$$

As in the fixed pay incentive scheme we analyzed previously, the above ICC states that the expected utility from exerting high effort should exceed the expected utility of shirking. The PC states that the expected utility from participation should exceed the utility associated with the outside option.

It is immediate to verify that the optimal performance-pay scheme, which minimizes the expected cost faced by the firm, is such that the ICC and the PC holds with strict equalities. Accordingly, the optimal values of $w_{H,i}$ and $w_{L,i}$, are found solving the following system of simultaneous equations:

$$w_{H,i}^a - w_{L,i}^a = \frac{e_H^b - e_L^b}{\alpha_i \Delta\sigma} \tag{13}$$

$$\sigma_{H,H}\alpha_i w_{H,i}^a + (1 - \sigma_{H,H})\alpha_i w_{L,i}^a = e_H^b \tag{14}$$

Importantly, (13) implies that the utility performance premium is decreasing in worker's productivity $\Delta\sigma$. A highly productive worker requires a relatively lower performance premium, $w_{H,i}^a - w_{L,i}^a$, to have the incentive to exert high effort compared to a low productivity worker because by exerting effort a highly productive worker is more likely to get the price than the low productivity one.

Combining (13) and (14) yields

$$w_{H,i} = \alpha_i^{-\frac{1}{a}} \left(e_H^b + (1-\sigma_{H,H}) \frac{e_H^b - e_L^b}{\Delta\sigma} \right)^{\frac{1}{a}}, \tag{15}$$

$$w_{L,i} = \alpha_i^{-\frac{1}{a}} \left(e_H^b - \sigma_{H,H} \frac{e_H^b - e_L^b}{\Delta\sigma} \right)^{\frac{1}{a}}. \tag{16}$$

We require $w_{H,i}, w_{L,i} > 0$, as we rule out the possibility that the firm could pay negative wages. Therefore, in all the subsequent analysis we impose the following

Assumption 2.

$$\frac{\sigma_{H,L}}{\sigma_{H,H}} < \frac{e_L^b}{e_H^b}.$$

This assumption sets an upper bound for $\sigma_{H,L}$ ($\sigma_{H,L}^{max} \equiv \sigma_{H,H}\frac{e_L^b}{e_H^b}$) and therefore, for a given value of $\sigma_{H,H}$, a lower bound for $\Delta\sigma$ given by

$$\Delta\sigma^{min} = \sigma_{H,H} - \sigma_{H,L}^{max} \equiv \sigma_{H,H}\frac{e_H^b - e_L^b}{e_H^b} \tag{17}$$

The expected value of the wage that the firm pays under the performance pay scheme is therefore given by

$$E(\omega_i) = \alpha_i^{-\frac{1}{a}} \left[\sigma_{H,H} \left(e_H^b + \frac{(e_H^b - e_L^b)(1-\sigma_{H,H})}{\Delta\sigma} \right)^{\frac{1}{a}} + (1-\sigma_{H,H}) \left(e_H^b - \frac{(e_H^b - e_L^b)\sigma_{H,H}}{\Delta\sigma} \right)^{\frac{1}{a}} \right] \tag{18}$$

It is crucial to note that, holding fixed σ_{HH}, the expected wage, $E(\omega_i)$, is an increasing function of $\sigma_{L,H}$ and, therefore, a decreasing function of the worker's productivity, as measured by $\Delta\sigma$. Specifically, computing the derivative of $E(\omega_i)$ with respect to $\Delta\sigma$ while holding fixed $\sigma_{H,H}$ such that it does not affect the probabilities associated with the performance-pay lottery ω, yields[11]

[11]Note that given $\Delta\sigma = \sigma_{HH} - \sigma_{LH}$, such a derivative is letting $\sigma_{L,H}$ vary to induce a variation in $\Delta\sigma$, while holding $\sigma_{H,H}$ constant. It is immediate to verify that the expression in square brackets on the RHS is strictly positive given $a \in (0,1)$.

$$\frac{E(\omega_i)}{d\Delta\sigma} = -\frac{\alpha_i^{-\frac{1}{a}}(e_H^b - e_L^b)\sigma_{H,H}(1-\sigma_{H,H})}{a\Delta\sigma^2}\left[\left(e_H^b + (1-\sigma_{H,H})\frac{(e_H^b - e_L^b)}{\Delta\sigma}\right)^{\frac{1-a}{a}} - \left(e_H^b - \sigma_{H,H}\frac{(e_H^b - e_L^b)}{\Delta\sigma}\right)^{\frac{1-a}{a}}\right] < 0 \tag{19}$$

which leads to the following result.

Lemma 1. *For any business model $i = O, R$, the higher the productivity of the worker within the firm, the less costly it is for the firm to pay the worker according to a performance-based scheme.*

Proof. The result follows immediately from equation (19), since the productivity of the worker, which is defined by equation (6), is an increasing function of $\Delta\sigma$.□

Risk aversion plays a crucial role in determining the above result. It is immediate to see that if the worker were risk-neutral ($a = 1$), the expected wage associated with the optimal performance pay scheme would be equal to $E(\omega_i) = \frac{e_H^b}{\alpha_i}$, which does not depend on the productivity of the worker, as measured by $\Delta\sigma$. Differently, as shown by equation (19), when the worker is risk-averse ($a < 1$), the expected wage that the firm has to pay under the optimal performance pay scheme decreases with the productivity of the worker. The reason is linked to the above discussion related to the lower performance premium needed to incentivize a more productive worker resulting from (13). Such performance premium is defined as the difference between the salaries attached to high and low signals, respectively. Using (15) and (16) it amounts to

$$w_{H,i} - w_{L,i} = \alpha_i^{-\frac{1}{a}}\left[\left(e_H^b + (1-\sigma_{H,H})\frac{e_H^b - e_L^b}{\Delta\sigma}\right)^{\frac{1}{a}} - \left(e_H^b - \sigma_{H,H}\frac{e_H^b - e_L^b}{\Delta\sigma}\right)^{\frac{1}{a}}\right]. \tag{20}$$

A lower performance premium means lower variability of the ex-post wage the worker earns, which, keeping the expected wage constant, implies a higher expected utility due to risk aversion. Accordingly, by reducing the performance premium needed to incentivize the worker, a higher value of the productivity of the worker, $\Delta\sigma$, allows the firm to save on the expected wage associated with the performance pay scheme. Differently, if the worker were risk-neutral, a reduction in the performance premium would not affect her expected utility, so the firm could not exploit the relationship between the performance premium and the expected salary to reduce the expected cost associated with the optimal performance pay scheme.

4 Firm's choice of business models and incentive schemes

In each period $t = 0, 1, 2$, the firm chooses the business model, $i = O, R$, and the worker's incentive scheme, $j = F, P$. At time 0, the firm will have to incur the cost associated with the fixed infrastructural investment necessary to implement any business model. Differently, at time $t \neq 0$, it can either stick to the "inherited" business model or switch to a new model, in which case it would have to implement it by paying the associated infrastructural fixed cost.

4.1 Firm's choice of the incentive scheme conditional on the business model

At any $t = 0, 1, 2$ and for a given business model $i = O, R$, the firm decides the optimal incentive scheme. Importantly, the adopted incentive scheme, conditional on being effective, does not affect the expected revenues, which are equal to $p_H Y$ per period, independently of whether the firm incentivizes the worker with fixed or performance pay. Moreover, there is no relationship between the fixed cost of implementing any business model and the cost of incentivizing the worker. As a result, in each period t, the optimal choice of the incentive scheme is the one that minimizes the expected wage that the firm has to pay in that period. Such expected wages are given by (10) for the fixed-wage scheme, F, and by (18) for the performance pay scheme, P.

Let

$$E(\omega_i|\Delta\sigma = \Delta\sigma^{min}) = \sigma_{H,H}^{1-\frac{1}{a}} \left(\frac{e_H^b}{\alpha_i}\right)^{\frac{1}{a}} \tag{21}$$

$$E(\omega_i|\Delta\sigma = \Delta\sigma^{max}) = \alpha_i^{-\frac{1}{a}} \left[\sigma_{H,H}\left(\frac{e_H^b - e_L^b(1-\sigma_{H,H})}{\sigma_{H,H}}\right)^{\frac{1}{a}} + (1-\sigma_{H,H})\left(e_L^b\right)^{\frac{1}{a}}\right] \tag{22}$$

the conditional expected values of wages under performance pay for the minimum and maximum values of the productivity of the worker, respectively. Then, the following result holds

Proposition 1. *For any given value of $\sigma_{H,H}$, under the business model i,*

1. *If*

$$E(\omega_i)|\Delta\sigma = \Delta\sigma^{max}) < w_i^F < E(\omega_i|\Delta\sigma = \Delta\sigma^{min}) \tag{23}$$

there exist a threshold $\Delta\sigma_i \in (\Delta\sigma^{min}), (\Delta\sigma^{max})$ for the worker's productivity, $\Delta\sigma$, such that *the firm chooses the performance pay scheme P if $\Delta\sigma \geq \Delta\sigma_i$ and fixed wage scheme F otherwise.*

2. *If*

$$E(\omega_i|\Delta\sigma = \Delta^{max}) > w_i^F \tag{24}$$

the firm always choose the fixed pay scheme F for any feasible value of the worker's productivity, $\Delta\sigma$.

3. *If*

$$w_i^F > E(\omega_i|\Delta\sigma = \Delta\sigma^{min}) \tag{25}$$

the firm always choose the performance pay scheme for any feasible value of the worker's productivity, $\Delta\sigma$.

Proof. At any time $t = 0, 1, 2$ and for a given business model $i = O, R$, the firm chooses performance pay P over fixed wage F if $E(\omega_i) \leq w_{F,i}$, where $E(\omega_i)$ is given by (18), and w_i^F by (10). Notice that while w_i^F does not depend on $\Delta\sigma$, $E(\omega_i)$ is strictly decreasing in $\Delta\sigma$ for given $\sigma_{H,H}$ as by (19). Also, for a given $\sigma_{H,H}$, the maximum value of $\Delta\sigma$ is when $\sigma_{H,L} = 0$, so $\Delta\sigma^{max} = \sigma_{H,H}$, while the minimum value of $\Delta\sigma$, $\Delta\sigma^{min}$, is given by (17)). Since $E(\omega_i)$ is monotonically strictly decreasing in $\Delta\sigma$ there is *at most* one threshold value of $\Delta\sigma^i \in (\sigma_{H,H}\frac{e_H^b - e_L^b}{e_H^b}, \sigma_{H,H})$ such that $E(\omega_i) = w_{F,i}$ and above (below) which the firm chooses the performance (fixed) pay scheme. This unique threshold value $\Delta\sigma_i$ exists if the $w_{F,i}$ is strictly included between the lower bound of $E(\omega_i)$, which is $E(\omega_i)|\Delta\sigma = \Delta\sigma^{max})$ and the upper bound of $E(\omega_i)$, which is $E(\omega_i|\Delta\sigma = \Delta\sigma^{min})$ where the values of these lower and upper bounds, expressed in (21) and (22), are obtained by replacing the values of $\Delta\sigma^{min}$ and $\Delta\sigma^{max}$ in (18). This proves point 1. of the proposition. Points 2 and 3 are straightforward elaborations of the latter □

The above Proposition is a key result of the model. It says that, for a given business model, the firm's choice of incentive scheme is related to the worker's productivity. As the expected cost of performance pay falls with the productivity of the worker, the firm might find it optimal to incentivize highly productive workers through performance pay and low productivity workers via fixed wage with monitoring. Importantly, Proposition 1 leads to the following

Corollary 1. *When it exists, the switching level of the worker's productivity above which the firm prefers performance to fixed pay is always higher when the worker works remotely than at business premises. That is,* $\Delta\sigma_O > \Delta\sigma_R$*.*

Proof. Assume (23) holds so that $\Delta\sigma_O$ and $\Delta\sigma_R$ exist, where given the definition provided in proposition 1 and equations (15) and (16), these two thresholds satisfy

$$\sigma_{H,H}\left(e_H^b + \frac{(e_H^b - e_L^b)(1-\sigma_{H,H})}{\Delta\sigma_O}\right)^{\frac{1}{a}} + (1-\sigma_{H,H})\left(e_H^b - \frac{(e_H^b - e_L^b)\sigma_{H,H}}{\Delta\sigma_O}\right)^{\frac{1}{a}} = \left(\frac{e_H^b - e_L^b}{\theta_O}\right)^{\frac{1}{a}} \quad (26)$$

$$\sigma_{H,H}\left(e_H^b + \frac{(e_H^b - e_L^b)(1-\sigma_{H,H})}{\Delta\sigma_R}\right)^{\frac{1}{a}} + (1-\sigma_{H,H})\left(e_H^b - \frac{(e_H^b - e_L^b)\sigma_{H,H}}{\Delta\sigma_R}\right)^{\frac{1}{a}} = \left(\frac{e_H^b - e_L^b}{\theta_R}\right)^{\frac{1}{a}} \quad (27)$$

Since the LHS of the above equations is decreasing in $\Delta\sigma_i$, for given $\sigma_{H,H}$, $\Delta\sigma_O > \Delta\sigma_R$ follows if $\left(\frac{e_H^b - e_L^b}{\theta_O}\right)^{\frac{1}{a}} < \left(\frac{e_H^b - e_L^b}{\theta_R}\right)^{\frac{1}{a}}$, which is always the case since, by assumption, $\theta_O > \theta_R$. $\square$

The above corollary tells us that performance pay, when feasible, is optimal for a wider range of worker's productivity in the 'remote' business model. This result is consistent with the empirical findings in Andres et al. (2023), according to which remote vacancies have a higher probability of involving some form of performance-based schemes than onsite vacancies.

The rest of the paper hinges on the assumption that a productivity switching value $\Delta\sigma_i$ always exists for both business models $i = O, R$ and therefore expression (23) holds.

4.2 Firm's choice of the business model at time $t = 0$

The previous section shows that, given the productivity of the worker, as measured by $\Delta\sigma$, there is only one pay scheme that is strictly preferred by the firm, regardless of the business model that the firm adopts. Importantly, given that the worker prefers working remotely, $\alpha_R > 1$, such an optimal pay scheme could be characterized by a higher expected wage under the business model O, than under R.[12] Accordingly, when deciding which business model(s) to implement at time $t = 0$, the

[12]This is indeed the case under performance pay, that is $E(\omega_R) > E(\omega_O)$ holds. Differently, in the case of the fixed pay scheme, whether $w_O^F > w_R^F$ holds or not depends on how effective remote monitoring is compared to monitoring in presence, i.e., it depends on the ratio, θ_R/θ_O.

firm takes into account the fact that the O model implies higher costs in terms of wages compared to R.

We can now state the following

Proposition 2. *At time $t = 0$ the firm chooses the business model O if and only if the cost, C_R, associated with the one-time infrastructural investment necessary to implement the business model R is high enough to satisfy the following condition*

$$C_R \geq 3[\min(E(\omega_O), w_O^F) - \min E(\omega_R), w_R^F)] + C_O \tag{28}$$

By contrast, the firm chooses the business model R if the opposite inequality holds.

Proof. The firm chooses the business model at time $t = 0$ by comparing the sum of the total expected costs in the three periods across all the possible combinations. Call $Z(i_0, i_1, i_2)$ the sum of total expected costs by the firm when choosing the business model i_0 at $t = 0$, i_1 at $t = 1$ and i_2 at $t = 2$. If in $t = 1$ and $t = 2$ the firm sticks to the inherited business model chosen in $t = 0$, this cost is given by

$$Z(i_0, i_0, i_0) = C_{i_0} + 3\min(E(\omega_{i_0}), w_{i_0}^F) \tag{29}$$

If $(i_0, i_1, i_2) \in \{(R, R, O), (R, O, R), (O, R, R)\}$ then the total expected costs are given by

$$Z(R, R, O) = Z(R, O, R) = Z(O, R, R) = C_R + C_O + 2\min(E(\omega_R), w_R^F) + \min(E(\omega_O), w_O^F) \tag{30}$$

Finally, if $(i_0, i_1, i_2) \in \{(R, O, O), (O, R, O), (O, O, R)\}$ then the total expected costs are given by

$$Z(R, O, O) = Z(O, R, O) = Z(O, O, R) = C_R + C_O + 2\min(E(\omega_O), w_O^F) + \min(E(\omega_R), w_R^F) \tag{31}$$

In order for business model O to be chosen in $t = 0$ and kept in $t = 1, 2$ the following conditions should be met

$$Z(O, O, O) < Z(R, R, R) \Leftrightarrow C_R > C_O + 3[\min(E(\omega_O), w_O^F) - \min(E(\omega_R), w_R^F)] \tag{32}$$

$$Z(O,O,O) < Z(R,R,O) \Leftrightarrow C_R > 2[\min(E(\omega_O), w_O^F) - \min(E(\omega_R), w_R^F)] \tag{33}$$

$$Z(O,O,O) < Z(R,O,O) \Leftrightarrow C_R > [\min(E(\omega_O), w_O^F) - \min(E(\omega_R), w_R^F)] \tag{34}$$

Inspection reveals that condition (32) is more stringent so that when (32) holds, also (33) and (34) hold. Also, since $Z(R,R,O) = Z(O,R,R)$ and $Z(R,O,O) = Z(O,R,O)$, then if condition (32) holds (O,O,O) is the optimal strategy and such condition is necessary and sufficient for the 'office' business model to be chosen in $t = 0$. By contrast, in order for business model R to be chosen in $t = 0$ and kept in $t = 1,2$ the following conditions should be met

$$Z(R,R,R) < Z(O,O,O) \Leftrightarrow C_R < C_O + 3[\min(E(\omega_O), w_O^F) - \min(E(\omega_R), w_R^F)] \tag{35}$$

$$Z(R,R,R) < Z(O,O,R) \Leftrightarrow C_R < (C_O - C_R) + 2[\min(E(\omega_O), w_O^F) - \min(E(\omega_R), w_R^F)], \tag{36}$$

$$Z(R,R,R) < Z(O,R,R) \Leftrightarrow C_R < (C_O - C_R) + [\min(E(\omega_O), w_O^F) - \min(E(\omega_R), w_R^F)], \tag{37}$$

It is immediate to verify that condition (36) reduces to $C_O + 2[\min(E(\omega_O) - \min(E(\omega_R), w_R^F), w_O^F)] > 0$ which is always true since $\min(E(\omega_R), w_R^F), w_O^F)] > 0$ holds as long as $\alpha_R > 1$. Equivalently, condition (37) reduces to $C_O + [\min(E(\omega_O), , w_O^F) - \min(E(\omega_R), w_R^F)] > 0$ which is also always true as long as $\alpha_R > 1$. Finally, conditions (32) and (35) are the opposite of the other, which proves the proposition. □

The above proposition identifies the condition that should be met in order for the firm to implement the O business model at $t = 0$. Intuitively, this condition states that the cost associated with the one-time infrastructural investment necessary to implement the R business model, C_R, should be large enough and, in particular, larger than the sum of the cost, C_O, associated with the correspondent infrastructural investment necessary to implement the O model plus the value of the potential cost savings due to the fact that expected wages paid under the R model might be lower than those paid under the O model, $3[\min(E(\omega_O), w_O^F) - \min(E(\omega_R), w_R^F)]$. Notice that if $C_R > C_O$ and if $E(\omega_O), w_O^F) < E(\omega_R), w_R^F)$ this condition is always met. Proposition 2 depends crucially on the assumption that the pandemic shock at time $t = 1$ is, ex-ante, an unforeseeable event characterized by a zero probability. In other words, Proposition 2 applies to the extent that the firm does not associate a positive probability to the pandemic shock that would cause the office model to be unviable in period $t = 1$.

Figure 1 illustrates the optimal strategy of the firm in $t = 0$ as a function of $\Delta\sigma$ when condition (28) holds. Note that, when condition (28), the model 'office' always dominates the model 'remote' irrespective of the incentive scheme. The situation described in Figure 1 aligns with the actual economies before the pandemic, as remote work was not widespread. Also, it is consistent with the evidence according to which performance pay applies more to highly productive workers (Eriksson and Villeval, 2008; Ewing, 1996).

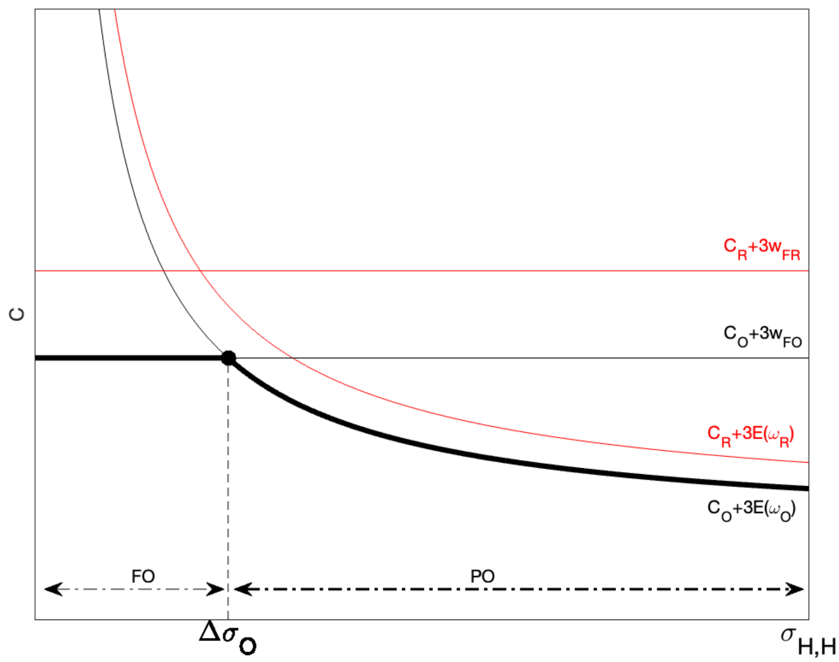

Figure 1: Optimal strategy of the firm in the pre-pandemic stage when condition (23) and (28) hold

4.3 The pandemic shock

We now turn to the analysis of the effects of the pandemic, assuming that condition (28) holds so that at time $t = 0$, the firm has implemented the O business model. At the beginning of period $t = 1$, the pandemic shock occurs, which prevents the firm from continuing to operate under that business model. The only possibility for the firm to continue operating is to implement the R

business model by incurring the infrastructural investment cost C_R. Recall that for simplicity and without much loss of generality, we assume that the firm knows that the pandemic ends at the end of $t = 1$ so that in $t = 2$, both business models are viable.[13]

We assume that if the firm stops the production process for a period, it cannot enter the market again and stays permanently out of business. Additionally, we assume that the model R is viable, i.e. the expected profits net of the infrastructural investment cost, C_R are positive. Formally

$$C_R + \min(\zeta_{F,R}; \zeta_{P,R}) + \min(\zeta_O; \zeta_R) < 2p_E Y_H, \tag{38}$$

Note that on the RHS, we consider the expected revenues of periods 1 and 2. Only by adopting the R model in period t could the firm generate revenues for $t \geq 1$ by avoiding going permanently out of business at $t = 1$. Once the firm has implemented the model R, it chooses the optimal incentive based on the productivity of the worker, $\Delta\sigma$, according to the logic of proposition 1. The following proposition describes the behavior of the firm at time $t = 1$.

Proposition 3. *At time $t = 1$, during the pandemic, the firm implements the 'remote' business model and pays the worker with fixed wage schedule if her productivity is below $\Delta\sigma_R$ and with performance-based pay if her productivity is above $\Delta\sigma_R$.*

Proof. Assuming that the firm goes permanently out of business if it stops operating during the pandemic ensures that the viability condition (38) is sufficient for the firm to choose to implement the model R. The rest of the proof then follows directly from the arguments developed in the above discussion and in proposition 1.□

Figure (2) illustrates the optimal strategy of the firm at $t = 1$ as a function of the worker's productivity, $\Delta\sigma$, given that in order to continue producing the firm has to switch to the R business model. The thicker line represents the optimal choice of the firm. As already discussed, the firm's only choice is about the incentive scheme to adopt.

[13] A more general approach would be to assume that the firm associates a non-negative probability to the event that the pandemic will go on in $t = 2$, and so the 'office' business model will not be available. Our results won't be qualitatively different.

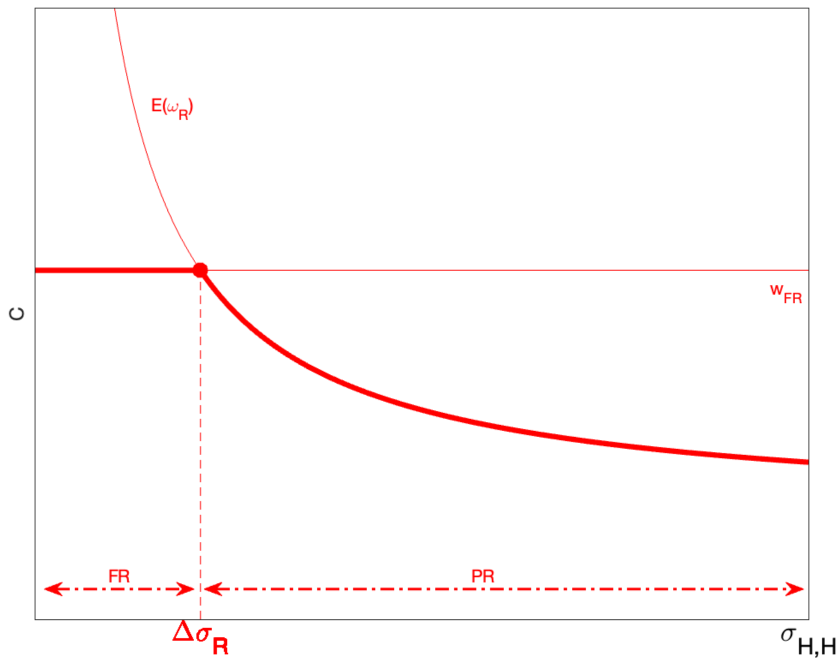

Figure 2: Optimal strategy of the firm in the pandemic stage

Proposition 3 has an immediate and straightforward corollary whose proof is self-evident after considering Corollary 1.

Corollary 2. *At time $t = 1$, as a consequence of the adoption of the R model due to the pandemic, the firm's choice of the incentive scheme compares to that of period $t = 0$, under the O model, as follows. If the worker's productivity $\Delta\sigma$ is included in the interval $(\Delta\sigma_R, \Delta\sigma_O)$, the firm gives up the F scheme and adopts the P one. By contrast, it sticks to the incentive scheme F if the worker's productivity $\Delta\sigma$ is included in the interval $(\Delta\sigma^{min}, \Delta\sigma_R)$. Finally, it sticks to P if the worker's productivity $\Delta\sigma$ is included in the interval $(\Delta\sigma_0, \Delta\sigma^{max})$.*

Proof. The proof follows directly from the fact that $\Delta\sigma_R < \Delta\sigma_O$, as stated by corollary 1.□ □

A relevant implication of the above result is that during the pandemic, if any, performance pay applies to a wider range of worker's productivity levels and provides a rationale as to why the pandemic performance pay has become more popular. Specifically, the widespread adoption of the

R model due to the pandemic has strengthened the case for performance pay since, under that business model, the monitoring of workers' effort required to implement fixed pay is less effective.

4.3.1 Post-pandemic

At time $t = 2$, after the pandemic, the firm has implemented both business models so that the related infrastructural costs are sunk. Accordingly, the firms' choice of which business model, $i = O, R$, and which incentive scheme, $j = P, F$, of business model and incentive scheme to adopt, i.e. the choice of which combination, $i, j \in \{O, R\} \times \{F, P\}$, to operate is made so to minimize the expected cost of labor. The following proposition holds

Proposition 4. *In $t = 2$, after the pandemic,*

- *If the worker's preference for remote work, measured by α_R, and/or the effectiveness of remote monitoring, θ_R, are sufficiently high, so that $\alpha_R > \frac{\theta_O}{\theta_R}$, the firm implements the business model R irrespective of the worker's productivity $\Delta\sigma$. As far as the incentive scheme is concerned, the firm applies F if the worker's productivity is low enough, i.e. $\Delta\sigma \in (0, \Delta\sigma_R)$, and P if the worker's productivity is high enough, i.e. for $\Delta\sigma \in (\Delta\sigma_R, \Delta\sigma^{max})$.*

- *By contrast, if $\alpha_R < \frac{\theta_O}{\theta_R}$ there exists a productivity value $\Delta\sigma^* \in (\Delta\sigma_R, \Delta\sigma_O)$ such that the firm adopts the combination $\{R, P\}$ if workers' productivity is sufficiently high $\Delta\sigma \geq \Delta\sigma^*$ while it implements the combination $\{O, F\}$ if sufficiently low $\Delta\sigma < \sigma^*$.*

Proof. Note that at time $t = 2$, the firm has implemented both business models. Therefore, it can either operate the "office" model or the "remote" model with no additional investment cost. Accordingly, the proof follows immediately from the comparison of the expected wage costs of the incentive schemes available under the two business models. □

The above proposition states the main results of the model regarding the structural change induced by the pandemic regarding remote work and performance pay. Remote work persists after the pandemic, and the case for performance pay is strengthened compared to the pre-pandemic situation. Return to office applies if the worker is not productive enough, so long as the effectiveness of the remote monitoring of the worker's effort and/or the worker's preference for remote work are sufficiently low. In this respect, the structural change induced by the pandemic features a

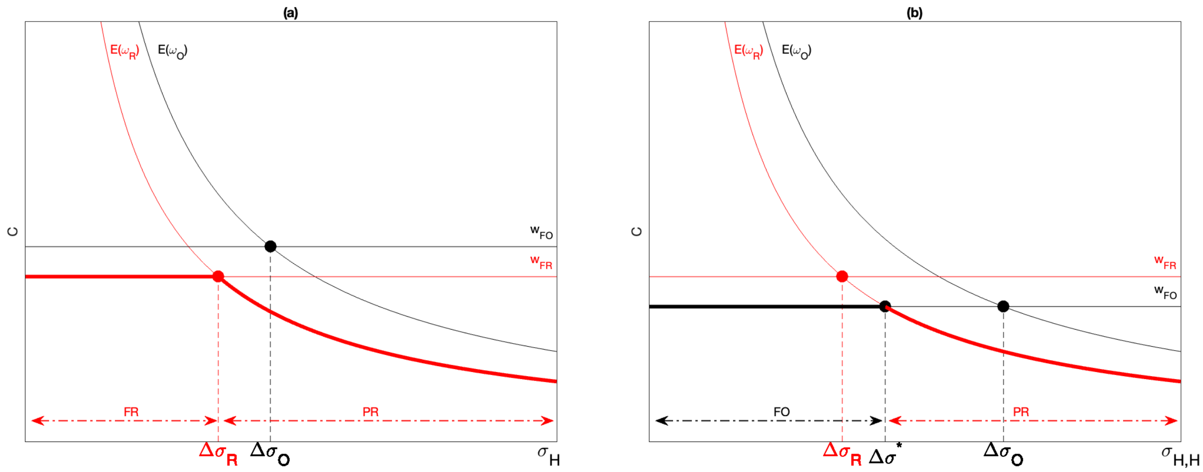

Figure 3: Optimal strategy of the firm in the post-pandemic era. Panel (a) illustrates the case when $\alpha_R > \frac{\theta_O}{\theta_R}$ while panel (b) depicts the scenario when $\alpha_R < \frac{\theta_O}{\theta_R}$.

productivity bias in the adoption of remote work, which is adopted only if workers' productivity is sufficiently high.

4.4 Empirical implications

As discussed in the previous section, in the post-pandemic phase, so long as the firm has incurred the fixed costs associated with the implementation of both business models, its choice of which model and incentive scheme to adopt depends on the worker's productivity, the effectiveness of remote monitoring of the worker's effort and the worker's preference for remote working. Specifically, the model suggests that an exogenous variation of a structural parameter, such as the effectiveness of remote monitoring of the worker's effort, captured by θ_R, could affect the firm's decisions. In reality, θ_R might vary across jobs, industries, institutional settings, states, and countries. Moreover, since technology, industrial organization, and institutional settings change as time goes by, the effectiveness of remote monitoring of workers' efforts might also change over time. Accordingly, the model predicts that the exogenous variation in the effectiveness of remote monitoring across different environments – whether jobs, industries, countries, or a job, an industry, or a country at different points in time – might be associated with different business models and incentive schemes being adopted by firms.

Proposition 5. *Consider two environments at $t = 2$, H and L, which differ in the effectiveness of remote monitoring of worker's effort equal to θ_R^H and θ_R^L, respectively, with $\theta_R^H > \theta_R^L$, such that $\alpha_R > \frac{\theta_O}{\theta_R^H}$ and $\alpha_R < \frac{\theta_O}{\theta_R^L}$ hold. Due to the lower effectiveness of remote monitoring of worker's effort, in L, compared to H,*

i. the O model and the F scheme is implemented for a wider range of low-productivity values (the interval $\Delta\sigma^{min}, \Delta\sigma^*$ in environment L vs. the empty interval in environment H)

ii. the R model and the scheme P is implemented for a wider range of high-productivity values (the interval $(\Delta\sigma^*, \Delta\sigma^{max})$ in environment L vs the interval $(\Delta\sigma_R, \Delta\sigma^{max})$ in environment H where $\Delta\sigma_R > \Delta\sigma^*$

Proof. It follows directly from proposition proposition 4 that: (1) in H, the firm chooses $i, j = R, F$ if $\Delta\sigma \in (0, \Delta\sigma_R^H)$ and $i, j = R, P$ if $\Delta\sigma \in (\Delta\sigma_R^H, \Delta\sigma^{max})$; (2) in L, the firm chooses $i, j = O, F$ if $\Delta\sigma \in (0, \Delta\sigma^*)$ and $i, j = R, P$ if $\Delta\sigma \in (\Delta\sigma^*, \Delta\sigma^{max})$. Therefore, it is immediate to verify that in L, the firm chooses model O model for a wider range of values of the worker's productivity than in H, where such a business model is never adopted, which proves part (i) of the proposition. Moreover, it is straightforward to see that $\Delta\sigma^* < \Delta\sigma_R^H$ where $\Delta\sigma_R^L$ is the productivity threshold above which, in L, having adopted model R, the firm prefers the incentive scheme P to F. This directly proves part (ii) of the proposition. □

Figure (4) illustrates how the firm's strategy changes with an exogenous variation in the effectiveness of remote monitoring of worker's effort, from θ_R^H to θ_R^L.[14] In the figure, fixed wage in the remote business model and environment H is denoted by w_{FR}^H, while in environment H it is denoted by w_{FR}^L. When the effectiveness of effort monitoring is high, i.e., $\theta_R = \theta_R^H$, the productivity threshold is denoted by $\Delta\sigma_R^H$, indicating that above this threshold, the firm applies performance pay, while below it adheres to a fixed wage schedule, maintaining the remote business model. However, a significant reduction in the effectiveness of monitoring, i.e., when $\theta_R = \theta_R^L$, alters the operational costs, making the fixed wage schedule with the remote business model more costly due to inefficiencies in monitoring the worker's effort. In other words, the costs associated with the fixed-wage

[14]However, the same figure can be considered while analyzing cross-state differences, where an economy is characterized by high and another by low effectiveness of remote monitoring.

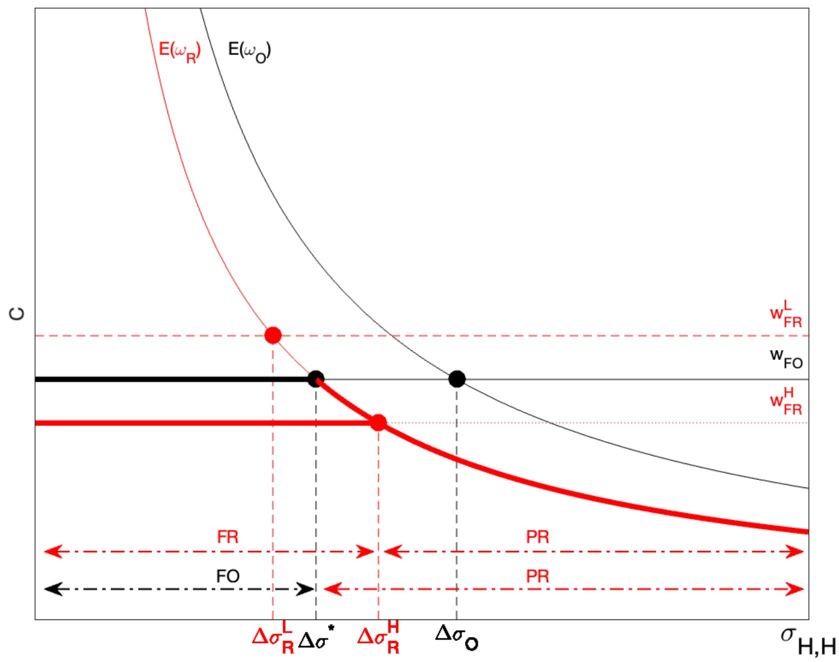

Figure 4: The optimal strategy for the firm when there is an exogenous variation in the effectiveness of monitoring effort, i.e. when θ_R changes from θ_R^H to θ_R^L.

schedule with the remote business model shifts up from w_{FR}^H to w_{FR}^L.

This exogenous variation in the effectiveness of effort monitoring changes the optimal strategy adopted by the firm, both in terms of the incentive scheme and the business model. Specifically, the productivity threshold determining the incentive scheme within the remote business model shifts from $\Delta\sigma_R^H$ to $\Delta\sigma_R^L$. However, the firm would prefer to change the business model to on-site for a low-productivity worker, as the reduction in the effectiveness of effort monitoring has made the on-site model more convenient for low-productivity, low-skill workers. Therefore, the relevant productivity threshold considered by the firm becomes $\Delta\sigma^*$, above which the firm will apply performance pay within the remote business model and below which it applies the fixed wage schedule within the on-site business model.

As a result, a significant reduction in the effectiveness of effort monitoring implies that remote work is implemented for a lower range of worker's productivity (because least productivity workers come back to the office) while performance pay is implemented for a wider range of worker's productivity (because the more productive workers among those who were previously paid with fixed wage are now paid by performance)

Figure 4 replicates two empirically relevant cases based on the US, which are extensively analyzed in the following sections. The first case is about the cross-state differences in laws regulating the remote monitoring of workers' effort by firms. The second case is about the introduction of new state laws that limit a firm's ability to remotely monitor the effort exerted by workers, for instance by requiring the firm to obtain explicit consent from the worker. Within the model, we interpret both cases as a reduction in θ_R. Suppose that in each state there is a multitude of firm-worker relationships, each of them described by our model, and allow for heterogeneity of workers' productivity across firms. Then, according to Proposition 5, the model predicts that in those states characterized by a sufficiently lower θ_R, a lower fraction of low-productive workers should work remotely as the firm finds it optimal to employ them (back) at the business premises. The same result should also hold, at state level, if θ_R falls due to the introduction of a more restrictive law. As detailed in the following section, we test such a prediction using both a pooled OLS and a DiD methodology. Our results support this key prediction of the model, thereby lending credibility to the mechanism we propose.

5 Empirical analysis

In this section, we illustrate the empirical analysis that focuses on testing one key prediction of the model uniquely tied to the main mechanism underlying the model results. We test such a prediction using the Survey of Working Arrangements and Attitudes dataset, SWAA henceforth (Barrero et al., 2021). The SWAA is a monthly survey conducted among 2,500 to 10,000 residents spread over all US' states, aged between 20 and 64, from 2020 onwards.[15] The SWAA dataset provides comprehensive information on various aspects related to working arrangements and attitudes, covering the extent of remote work and providing insights into its prevalence among workers and firms' strategies.

[15] The dataset is currently updated monthly. See: `https://wfhresearch.com/data/`. The results reported in this version of the draft are produced using release of the dataset that includes information from May 2020 to February 2024.

Proposition 5 implies that, in a post-pandemic scenario, as the effectiveness of remote monitoring falls, the firm's choice of incentive scheme and business model might change. Specifically, a sufficient decrease in remote monitoring effectiveness, from θ_R^H to θ_R^L, reduces the productivity threshold above which the firm adopts performance pay and makes the office business model comparatively more favorable for workers with low enough productivity. As a result, we should observe a reduction in remote work because low-productivity workers return to the office and an increase in the utilization of performance-based incentive schemes for those working remotely. Accordingly, the same holds while comparing regions which differ in term of effectiveness of remote monitoring. If a state is characterized by low effectiveness, we should observe less remote work for low-skill workers there with respect to a comparable state where the effectiveness is high.

Electronic monitoring is a common practice in the United States.[16] Unlike in other countries, in US employers have substantial rights to oversee their employees' activities.[17] At the federal level, there are laws providing the main principles regulating this widespread practice but do no set specific rules. Therefore, states can implement their own laws, potentially creating heterogeneity across US. In our empirical analysis, we interpret state laws that mandate employers to inform or obtain consent from employees about electronic monitoring as a reduction in the effectiveness of remote monitoring, all else being equal. In other words, such laws replicate the transition from a state of the world where the remote monitoring effectiveness is high, i.e. $\theta_R = \theta_R^H$, to a state where such effectiveness is low, hence $\theta_R = \theta_R^L$. Based on such interpretation, we exploit the heterogeneity in the state legislation within the US discussed above to test the prediction of the model that reduced efficacy of remote monitoring should lead to reduced remote work for low productivity workers.

First, we run an Ordinary Least Squares (OLS) regression, to investigate the long-run correlation between restrictive legislation on workers' monitoring and the share of remote work days relative to total working days. In doing so, we exploit the heterogeneity across US states with respect

[16] Despite the lack of direct evidence on this aspect, anecdotal proofs are provided by the rich supply of monitoring software solutions from US-based companies and forums discussing the matter.

[17] In Europe, for example, employers can monitor their workers for legitimate purposes and comply with the principles of fairness, proportionality, and subsidiarity. In addition, notice is an essential requirement imposed under the General Data Protection Regulation (GDPR).

to the legislative framework. Second, for a tentative causal identification of the effect on remote work days, we leverage the exogenous variation in legislation about electronic monitoring within the state of New York to estimate a triple Diff-in-Diff approach. The triple Diff-in-Diff allow us to isolate the effect identification from within-state spillover effects and across-state differences in economic fundamentals. However, results hold through when we perform robustness by estimating the a classic Diff-in-Diff, where we compare the differences in remote work between low-skill in NY and the rest of us.

5.1 Employee Monitoring in US

Employee monitoring in the United States is a widespread practice, with employers having considerable rights to monitor their employees' activities. Employers use various methods to monitor their workers. Among those, the most relevant to our analysis is the use of monitoring software applied to company's and personal electronic devices. Employers use such a monitoring software to track employee activities, including computer usage, internet activities, email content, and keystrokes. These software solutions are standardized and provided by third parties, which ensures adherence to legal requirements and company policies.

The legal landscape of employee monitoring in the US is heterogeneous because, despite there exist federal laws outlining the principles to regulate the phenomenon, state legislatures are free to establish their own rules. At the federal level, the Electronic Communications Privacy Act (ECPA), Computer Fraud and Abuse Act (CFAA), and Stored Communications Act (SCA) provide the main principles which have to be observed all over US. In general, according to federal legislation, employers can monitor workers without notify or demand the consent of their employees. However, certain states have implemented their own laws on this matter. Connecticut, Delaware, New York, and California have stringent privacy laws which require employers to ask the consent or notify their employees about the electronic monitoring undertaken.[18] We interpret the requiring of notice

[18] With the Public Act no. 98-142, approved on the 4th of June 1998, employers in Connecticut are required to notify their employees of electronic monitoring. The code title 19 Labor 705, approved on the 10th of July 2001 with the house bill no. 75, imposes employers in Delaware to notify employees of monitoring of telephone transmissions, electronic mail and Internet usage. The state of California introduced privacy protection for consumers with the California Consumer Privacy Act of 2018, amended with the California Privacy Rights Act (CPRA) in November 2020 that extends the protection to employees but that is effective since January 2023. In New York, a law requiring employers to notice employees about the type of monitoring they perform went into effect in May 2022.

or consent as a restrictive regulation that makes remote monitoring less effective for the employers. The idea is that the worker, informed about the kind of monitoring activities implemented by the employer, can take countermeasures and find ways to evade the remote monitoring system. A complementary alternative could be that, once the employer is forced to inform workers about the monitoring, she decides to avoid most invasive (and thereby more effective) monitoring practices in order to preserve workers' loyalty. Finally, should the worker refuse to provide the consent to monitoring activities by the employers, the latter is left with the options of either employing the worker remotely without monitoring or imposing a return to the business premises. In any case, the result is a restriction of the employer's possibility set. Therefore, we label states which implemented such a law as 'treated' and therefore where the effectiveness of remote monitoring is low, i.e. where $\theta_R = \theta^l_R$. We exploit the heterogeneity across States legislation to evaluate the long-run correlation of more restrictive regulation on the share of remote work paid days performed by employees.

Table 6 reports the summary statistics relative to the sample employed for the pooled OLS, that span from July 2020 to January 2024. Remote work is substantial and pervasive across all education levels. However, as documented by the literature on remote work (Barrero et al., 2021), more educated workers have a higher share of days worked outside the business premises than low-educated. Figure B.2, instead, visually displays the heterogeneity of average remote work across US' states. Remote work is also pervasive across states, however it is dispersed as it ranges from almost 60% to little more than 20%.

Driven by the prediction of the model, the idea is that regulations on remote monitoring likely impact the share of remote work days only for low-productivity workers, as the firm firm prefers to bring them back at the business premises paying them with the fixed wage scheme, if the regulation make the remote monitoring ineffective enough. Most high-productivity workers are not affected by the effect of the legislation because the firm still finds optimal to incentivize them through a performance pay scheme. As a result, the effect of the legislation on remote work depends on workers' skills, which motivates the identification adjusted by skills. As specified later, we proxy skills using the level of education. To investigate the relationship between a more restrictive regulation and the share of remote work paid days performed by worker i at time t we estimate the following specification

$$Y_{i,t} = \alpha + \beta_1 legal_i + \beta_2 lowskill_i + \beta_3 legal_{i,t} \times lowskill_i + X'_{i,t}\delta + A'_{i,t}\gamma + \epsilon_{i,t}, \tag{39}$$

where $Y_{i,t}$ represents the share of remote work paid days of worker i at time t, $legal_i$ is a dummy indicating if worker i resides in a state that has a restrictive regulation on employees monitoring, i.e. 'treated' state, $lowskill_i$ is a dummy indicating whether the worker is low-skill (proxied by education), $X_{i,t}$ is a vector of controls, $A_{i,t}$ is the full set of fixed effects (time, age, industry, and state), and $\epsilon_{i,t}$ is an error term. As anticipated, the legal dummy takes value one if the worker resides in a state that implemented restrictive regulation on workers monitoring by at least requiring the consent or notice to employees of such monitoring, zero otherwise.[19] The vector of controls further includes the legal dummy, the low-skill dummy, log of the income, the gender dummy, the number of children, the interaction between gender and children, and the internet quality.[20] Errors are clustered at the state-level, and the weights provided with the SWAA are used. We define low-skill workers those who did not obtain their college degree, high-skill otherwise. The coefficient of interest is the one associated to the interaction between the *legal* and *lowskill* variables, β_3, which measures the correlation of a more restrictive regulation on the share of remote work days performed by a low-skill worker relative to the high-skill. A negative coefficient would suggest that when a state imposes a more restrictive regulation on monitoring employees, the share of remote work days performed by low-skill workers is lower with respect to high-skill workers.

Results are reported in Table (1). Columns (1) reports the results by estimating equation (39) without controls and fixed effects that are added in column (2). As the results suggest, in general, low-skill workers perform fewer hours of remote work, which is consistent with the well-documented evidence about the concentration of remote work among more educated and experienced workers (Barrero et al., 2021). More in general, remote work is a practice more popular among more educated, richer females with children and in places where the internet connection is reliable. Inter-

[19] The legal dummy is equal to one if the worker resides in Connecticut and Delaware, while only from May 2022 onwards if it resides in New York. We drop observations for workers residing in the state of California because is not clear whether, previous to the CPRA, the CPPA and other laws (such as the bill entitled "AB 1651") restricted employees' monitoring. However, results hold also by including those and are available upon request.

[20] The internet quality is measured as the fraction of time the internet works as asked to respondents.

	(1)	(2)
Dep. Var.	% remote work	% remote work
Legal	8.464***	4.064***
	(1.634)	(0.691)
Low-skill	-17.88***	-9.273***
	(1.025)	(0.761)
Legal × Low-skill	-5.830***	-4.169***
	(1.608)	(0.986)
Constant	51.41***	49.72***
	(1.215)	(0.614)
Observations	82,907	82,907
R-squared	0.042	0.123
Controls	NO	YES
Fixed effects	NO	YES
Clust. errors	State-level	State-level

Table 1: Controls include the log of the income, the gender dummy, the number of children, the interaction between gender and children, and the internet quality. Continuous variables are normalized to mean zero. Fixed effects include time, age, industry and state. Robust errors are clustered at the state level and reported in parentheses. (*** $p<0.01$, ** $p<0.05$, * $p<0.1$)

estingly, the coefficient that captures the share of remote work days in treated states is significant and positive, suggesting that in those states, the practice of remote work is more extensive than in others. Indeed, states that regulate remote working are those with an higher conditional average of days worked remotely and possibly where remote was a widespread practice even before the pandemic. The effect of residing in a state where remote work is a widespread practice is almost canceled for low-skill individuals by the introduction of the monitoring regulation. Notably, the coefficient for the interaction is significantly negative and holds beyond age, industry, state and over time. It suggests that, on average, low-skill workers residing in treated states have a 4% lower share of remote working days over the total of working days, with respect to high-skill workers. This result is in line with the theoretical prediction outlined in proposition 5, according to which in those states characterized by a sufficiently lower effectiveness of remote monitoring, a lower fraction of low-productive workers should work remotely, as the firm finds it optimal to mandate a return to the office for them. In other words, cross-state difference in the effectiveness of remote monitoring can explain why in treated states there are less low-skill working remotely.

5.2 The case of New York state

The case of New York presents a compelling opportunity for investigation. Unlike Connecticut and Delaware, which had already taken steps to regulate the electronic monitoring of employees even before the pandemic, the states of New York introduced restrictions only after 2020 after the onset of remote work due to the pandemic. Specifically, with the bill S2628 that became law the 7th of May 2022, the state of New York aimed to regulate electronic monitoring by employers. The introduced legislation requires employers engaging in monitoring to provide prior written notice to their employees upon hiring and once annually.[21] It seeks to protect employee privacy and ensure transparency in monitoring practices. By notifying employees of electronic monitoring, employers make the former aware about the consequences of inappropriate activity. This knowledge increases transparency within organizations and reduces the likelihood of lawsuits regarding invasion of privacy. Additionally, informing them of surveillance practices, enables employees to make informed decisions about their activities during working hours.

The bill was initially referred to the Codes Committee on January 22, 2016, indicating ongoing legislative consideration. According to the bill's provisions, it would take effect on the one-hundred-eightieth day after its enactment into law. This implies that upon successful passage through the legislative process and subsequent signing into law by the appropriate authorities, it would become effective after 180 days. With the bill being signed on the November 2021, the law officially took effect on May 2022. This provision allows employers a reasonable transition period to adjust their practices and adhere to the new requirements outlined in the legislation.[22] As pointed out previously, we interpret the requiring of notice as a restrictive regulation that makes monitoring less effective for employers. Again, the idea is that the worker, informed about the kind of monitoring activities

[21] The Attorney General may enforce the provisions of this law, and violators may be subject to a maximum penalty of $1,000 for each offense. Exemptions are provided for processes performed solely for computer maintenance and/or protection.

[22] However, it's worth noting that the bill was first proposed in 2009 but, since then and despite numerous attempts, it never went beyond the third reading. A third reading is the stage of a legislative process in which a bill is read with all amendments and given final approval by the legislative body. Solely with the most recent version, in October 2021 the bill was delivered to the Governor for the signature. Considering the narrow and dynamic nature of New York's social and political landscape, where public opinion circulates rapidly, anticipation of the law's effects may have begun earlier than its official enactment date, potentially affecting the empirical analysis.

implemented by the employer, can act to evade the monitoring system. Furthermore, once the employer is forced to inform workers about the monitoring she can decide to avoid most invasive (and thereby more effective) monitoring practices in order to preserve employees' loyalty. In both cases, the result is a restriction of the employer's possibility set to monitor workers.

The introduction of this new law creates a discontinuity on the legislative framework that happen to be within the time-frame in which we observe information on remote work.[23] The discontinuity offers an appealing empirical setting to identify causally the mechanism formalized in proposition 5. Therefore, we exploit this exogenous variation in the legislation to evaluate causally the effect of a reduction in the monitoring effectiveness on the share of remote work days, through a Diff-in-Diff analysis. Inspired by the prediction of the model (see proposition 5), we believe the effect of the legislation is restricted on low-skill workers. Following the reasoning outlined for the pooled OLS, the idea is that regulations on monitoring likely impact only the subset of low-productivity workers. The firm, following a sufficient reduction in the effectiveness of monitoring, prefer to mandate a return to the office and apply a fixed wage scheme because remote work becomes too costly. Conversely, high-productive workers are likely not affected because the firm still prefer to exploit their risk aversion to pay them a relatively low performance premium, since form them exerting high-effort is less costly in terms of expected utility. Therefore, also in the DiD analysis the effects are dependent on workers' productivity, which motivates the identification adjusted by education which is the proxy use for our productivity measure.

Table 8 presents the summary statistics about the state of New York and the rest of US for the period used for the Diff-in-Diff estimation, specifically from December 2021 to November 2022. As previously mentioned, New York state exhibits an above-average share of remote work days compared to other states (see also Figure B.2). Not only New York workers go to the office less frequently, but they are also, on average, more educated, younger, and with higher income. Tables 7 and 9 compare pre- and post-treatment periods for NY and the rest of US, respectively. There are not striking differences across periods, where remote work increases slightly for both.

To evaluate the causal effect of a more restrictive regulation on the share of remote work paid

[23] Unlike the case of Delaware and Connecticut, that introduced the previously cite laws before 2020, year since when we have detailed information on remote work.

days for low-skilled workers, we estimate a triple Diff-in-Diff model. Not only we consider the difference between New York and rest of US workers, but also between low- and high-skill workers. The triple interaction let us avoid biases arising from persistent economic differences across states and within-state spillover. An alternative approach would be to estimate a simple Diff-in-Diff by comparing high-skill and low-skill workers within the New York state. However, this would not be robust as long as the legislation has within-state spillovers. An example of within-state spillovers could be that, upon the reduction of monitoring effectiveness for low-skill workers the employer mandate a generalized return to office, with high-skill workers call back to the business premises together with low-skill for better workflow coordination. Another avenue can be also to compare low-skill workers in New York with low-skill workers in other non-treated states but this would not be valid if states are characterized by different economic conditions and hence trend differently. As a robustness check, we perform an alternative specification and report in Appendix A.2 the results of the DiD on the subsample of low-skill workers, which compare New York with respect to the rest of US. To establish the counterfactual with a triple Diff-in-Diff model, we estimate the following specification

$$\begin{aligned} \mathrm{Y}_{i,t} = \quad & \alpha + \beta_1 \mathrm{Post}_t + \beta_2 \mathrm{NY}_i + \beta_3 \mathrm{lowskill}_i + \beta_4 \mathrm{Post}_t \times \mathrm{NY}_i + \beta_5 \mathrm{Post}_t \times \mathrm{lowskill}_i \\ & + \beta_6 \mathrm{NY}_i \times \mathrm{lowskill}_i + \beta_7 \mathrm{Post}_t \times \mathrm{lowskill}_i \times \mathrm{NY}_i + X'_{i,t}\delta + A'_{i,t}\gamma + \epsilon_{i,t}, \end{aligned} \tag{40}$$

where $Y_{i,t}$ represents the share of remote work paid days performed by worker i at time t, NY_i is a dummy equal to 1 if individual i resides in the state of New York, $Post_t$ is a dummy equal to 1 after May 2022, $lowskill_i$ is a dummy equal to 1 indicating whether the worker is low-skill (where skill is proxied by education), $X_{i,t}$ is a vector of controls, $A_{i,t}$ is the full set of fixed effects (time, age, industry and state), and $\epsilon_{i,t}$ is an error term.[24] The vector of controls includes the log of the

[24]The inclusion of fixed effects implies that β_1 and β_2 are dropped due to multicollinearity.

income and the gender dummy.[25][26] Errors are clustered at the state level, and the weights provided with the SWAA are used. As before, we define low-skill workers those who have up to 3 years of college. Since the period is characterized by high uncertainty, in order to avoid confounding biases we restrict the sample for the estimation by considering a 6-months window, 6 months before and 6 after the treatment date. Hence, the sample goes from December 2021 to November 2022.

The coefficient of interest is β_7, which captures the difference between (i) the change in the share of remote work days of low-skill and high-skill workers in New York post- and pre-treatment with respect to (ii) the change in the share of remote work days of low-skill and high-skill workers in the other states. A negative coefficient would indicate that, subsequent to the introduction of the legislation, low-skilled workers in NY decreased their share of remote work paid days relative to high-skill more than what, in other states, low-skill workers did compared to high-skill. In other words, a negative β_7 suggests an adverse effect of the legislation on the share of remote work paid days for low-skill workers in the treated state. Results reported in Table (2) shows that the effect is negative and significant, establishing at around 4%. It suggests that, after the implementation of the legislation in the state of New York, there has been a 4% decrease in the share of remote work relative to total working days for low-skill workers.[27] The estimates provide additional and more robust evidence about the empirical prediction of the model, outlined in proposition 5, according to which a sufficient decrease in monitoring effectiveness induce low-skill workers to return to the office.

Figure 5 reports the event-study that shows the changes in the outcome variable for low-skill workers, i.e. the β_7, around the treatment date. The estimates in the pre-treatment period, i.e. before May 2022, are zero such that validate the parallel trends assumption. During the post-

[25] As pointed out in Olden and Møen (2022), the inclusion of control variables with substantial explanatory power increase the accuracy of the estimate and reduce the residual variance not explained by the econometric model. Furthermore, it does account for compositional differences which may be present across states, which is the case in our setting (see figure B.2). However, with respect to the estimate of Equation (39), some controls are excluded in order to preserve observations around the date of the treatment.

[26] Following Pei et al. (2019), we test that the introduction of such controls are not poor measures of the potential underlying confounders. To do so, we perform a balancing test which verify the joint significance of the triple interaction coefficient in a set of specifications, where regressors are put as the outcome variable on the LHS once a time. The F-test reveals that we cannot reject the null hypothesis according to which the triple interaction coefficient is equal to zero. It confirms that coefficient of interest is not affected by the inclusion of those regressors and fixed effects in the regression.

[27] Appendix A.1 reports the results estimating equation (40) using a 24-months window, and results hold.

Dep. Var.	(1) % remote work	(2) % remote work
NY	16.54***	
	(1.311)	
Post	-0.365	
	(0.932)	
Low-skill	-16.40***	-8.921***
	(1.180)	(1.274)
NY × Post	-1.236	0.548
	(0.932)	(1.021)
NY × Low-skill	-7.395***	-3.725***
	(1.180)	(1.063)
Post × Low-skill	1.046	1.787
	(1.353)	(1.285)
NY × Post × Low-skill	-2.674*	-4.090***
	(1.353)	(1.321)
Constant	47.35***	47.87***
	(1.311)	(0.562)
Observations	44,738	44,738
R-squared	0.044	0.130
Controls	NO	YES
Fixed effects	NO	YES
Clust. errors	State-level	State-level

Table 2: Triple DiD on mandated notice of monitoring in the State of New York. The estimation is performed in a 12-month window, 6 months before and after the treatment. Controls include the log of the income and a dummy for gender. Fixed effects include age, time, industry, and state. Continuous variables are normalized to mean zero. Robust errors are clustered at the state level and reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

treatment period, starting from May 2022 onwards, it is observed that only the treatment period exhibits a positive coefficient on the number of remote hours worked by low-skilled individuals. This phenomenon could be attributed to the fact that the legislation does not take full effect at the start of the month, but rather from May 7th onwards. Furthermore, the legislator allows some discretion to employers, as any employer found in violation of the law may face civil penalties, starting from five hundred dollars for the first offense, escalating to one thousand dollars for the second offense, and three thousand dollars for subsequent offenses. However, the other post-treatment periods show negative or zero coefficients, indicating that the implementation of the legislation has a scattered yet consistently negative effect over time. The effect estimated with the triple Diff-in-Diff supports the mechanism outlined in proposition 5.

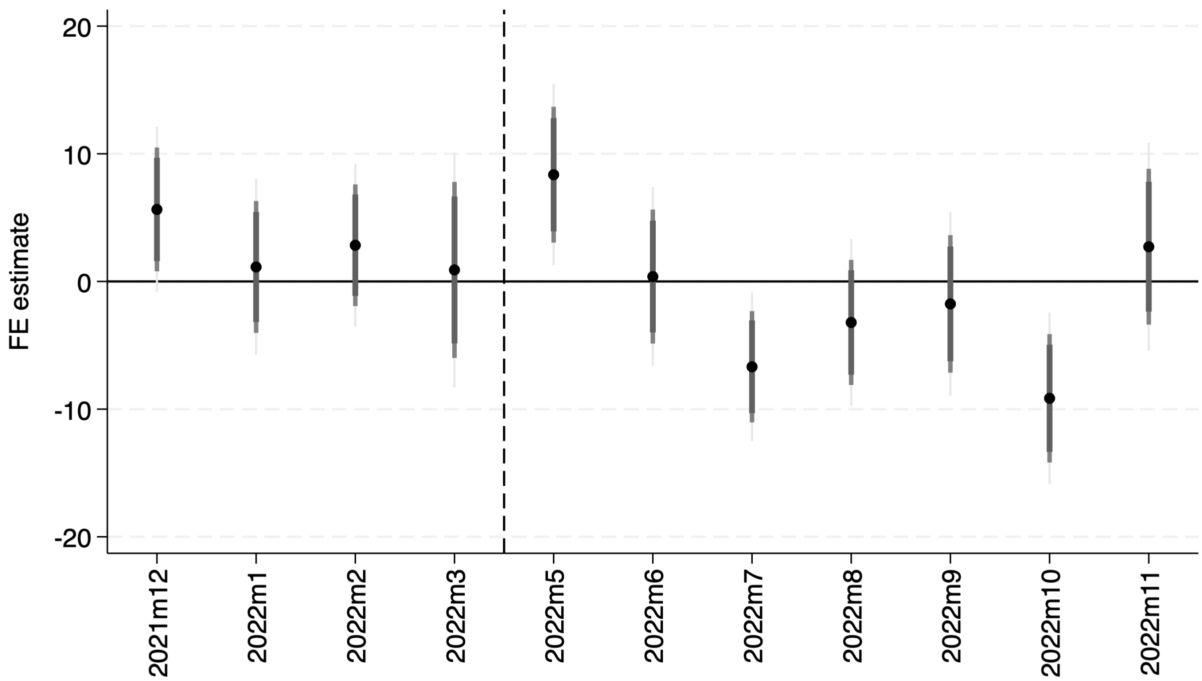

Figure 5: Event-study for low-educated workers for the 12-months window estimation. Estimates are with respect to the month preceding the treatment date, i.e. April 2022. From the darkest to the lightest gray, the shades depict the 90%, 95%, and 99% confidence intervals, respectively.

6 Conclusion

We provide a parsimonious model that rationalizes the evidence about the increased popularity of remote work and performance pay during and after the pandemic and their persistence in the aftermath of the pandemic. The model features a key prediction stemming from its key mechanism. A decrease in the effectiveness of monitoring workers' efforts under remote work reduces remote working for relatively low-skill workers. We find strong empirical support for such a prediction, which more generally provides support for the key mechanism underlying the model. The simplicity of the setup allows for insightful extensions in various directions including firm entry, wage determination in labor markets populated by many workers and firms, as well as firms' and workers' heterogeneity and skill-biased technological progress. Our analysis indicates that pandemic health policies and regulations could have a significant structural effect on the diffusion of remote work and performance pay.

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Appendix

A Robustness checks

A.1 Triple DiD for 24-months

	(1)	(2)
Dep. Var.	% remote work	% remote work
NY	14.23***	
	(1.120)	
Post	-3.435***	
	(0.782)	
Low-skill	-16.88***	-9.049***
	(0.837)	(0.718)
NY × Post	3.156***	4.378***
	(0.782)	(0.839)
NY × Low-skill	-9.110***	-5.705***
	(0.837)	(0.653)
Post × Low-skill	2.107**	2.388***
	(0.943)	(0.887)
NY × Post × Low-skill	-4.705***	-5.715***
	(0.943)	(0.983)
Constant	49.16***	47.60***
	(1.120)	(0.431)
Observations	93,115	93,115
R-squared	0.045	0.127
Controls	NO	YES
Fixed effects	NO	YES
Clust. errors	State-level	State-level

Table 3: Triple DiD on mandated notice of monitoring in the State of New York. The estimation is performed in a 24-month window, 12 months before and after the treatment. Controls include the log of the income and a dummy for gender. Fixed effects include age, time, industry, and state. Continuous variables are normalized to mean zero. Robust errors are clustered at the state level and reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 3 shows that results hold also by using a 24-months window, i.e. 12 months before and 12 after the treatment date, to estimate equation (40). More precisely, the coefficient of interest, β_7, displays a significant and negative coefficient slightly higher with respect to the estimation with the 12-months window. However, the positive and significant coefficient for the interaction between NY and $Post$ raises the following concern. The β_7 coefficient is estimated taking the difference between (i) the change in the share of remote work days of low-skill and high-skill workers in New York post- and pre-treatment with respect to (ii) the change in the share of remote work days of low-skill and high-skill workers in the other states. Therefore, an increase in the share of remote work for high-skill workers, captured by the positive and significant coefficient for the interaction between NY and $Post$, can possibly drive mechanically down our coefficient of interest. This possibility arises because the triple DiD specification do not take into account differences in trends across (skill) group. However, considering the results in table 2, obtained by considering a 12-months window which somehow limit the extent of uncertainty and possible confounding biases, the increasing share of remote work for high-skill workers seem to be not a problem. Furthermore, to provide additional robustness checks which addresses that concern, in appendix A.2 we estimate a DiD on the sub-sample of low-skill workers which rule out any bias coming from different trends across skill groups.

Figure A.1 reports the event-study that shows the changes in the outcome variable with respect to the treatment for low-skill workers, i.e. the β_7, around the treatment date, using the 24-months window. The estimates in the pre-treatment period, i.e. before May 2022, are zero such that the parallel trends assumption is validated again.

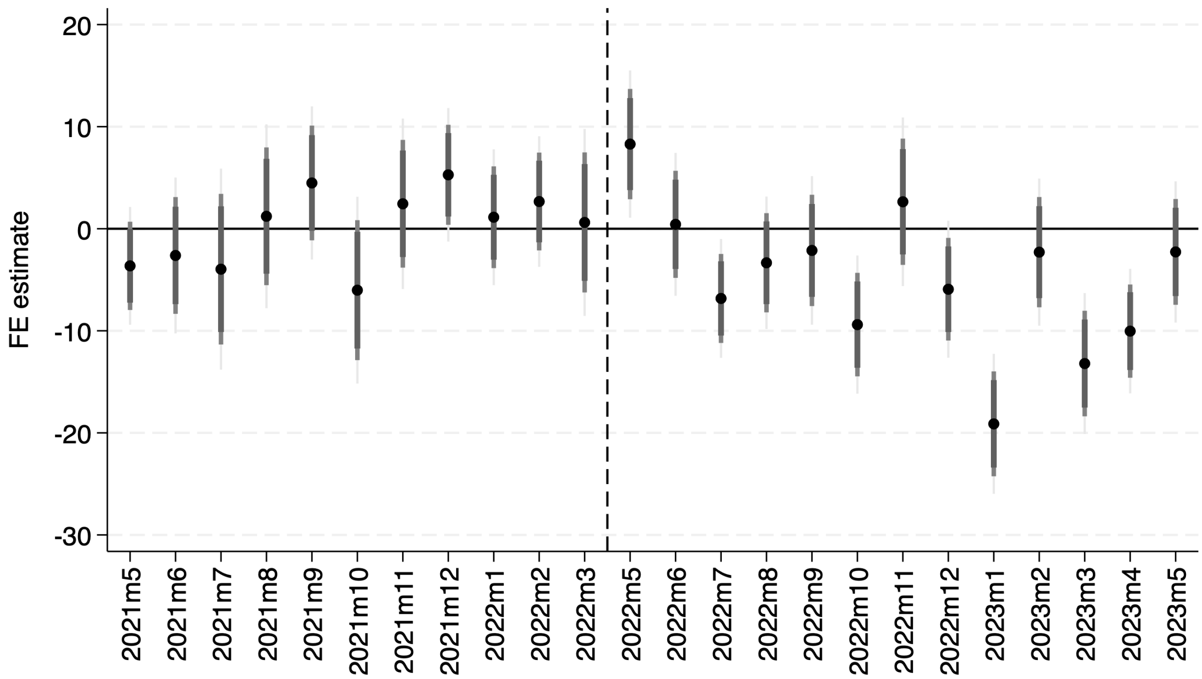

Figure A.1: Event-study for low-educated workers for the 12-months window estimation. Estimates are with respect to the month preceding the treatment date, i.e. April 2022. From the darkest to the lightest gray, the shades depict the 90%, 95%, and 99% confidence intervals, respectively.

A.2 DiD on low-skill workers

To address the concern that the results in table 3 might be driven by high-skill trending upward with respect to low-skill, therefore mechanically making the β_7 negative, we estimate a Diff-in-Diff on the subsample of low-skill workers. By restricting the sample to low-skilled workers, we estimate the average treatment effect by taking the relative differences of treated (low-skill New Yorkers) and control (low-skill in the rest of US) with respect to the the share of remote work post- and pre-treatment. The estimation of the average treatment effect tells us what is the effect of the restrictive regulation, introduced in New York, on the share of remote work days over total working days for low-skill workers. This estimation cannot take into account persistent economic differences across state, that however can be attenuated by time and state fixed effects. To establish the counterfactual, we estimate the following specification

$$Y_{i,t} = \alpha + \beta_1 \text{Post}_t + \beta_2 \text{Treat}_i + \beta_3 \text{Post}_t \times \text{Treat}_i + X'_{i,t}\delta + A'_{i,t}\gamma + \epsilon_{i,t}, \qquad (A.1)$$

where $Y_{i,t}$ represents the share of remote work paid days performed by worker i at time t, $Post_t$ is a dummy equal to 1 after May 2022, $Treat_i$ is a dummy equal to 1 if the worker reside in the state of New York, $X_{i,t}$ is a vector of controls, $A_{i,t}$ is the full set of fixed effects (time, age, industry and state), and $\epsilon_{i,t}$ is an error term. Importantly, we restrict the sample on low-skill workers using education as a proxy. Therefore, the sub-sample is composed by workers who do not have a college degree. The vector of controls includes the log of the income, years of education and the gender dummy.[28] Errors are clustered at the state level, and the weights provided with the SWAA are used. Since the period is characterized by high uncertainty, in order to avoid confounding biases we restrict the sample for the estimation by considering a 12-months window, 6 months before and 6 after the treatment date.[29] Hence, the sample goes from December 2021 to November 2023.

The coefficient of interest is β_3, corresponding to the interaction between $Treat$ and $Post$, which captures the difference between (i) the change in the share of remote work days of low-skill post- and pre-treatment in the treated state, New York, and (ii) the change in the share of remote work days of low-skill post- and pre-treatment in the control states. A negative coefficient would indicate that, subsequent to the introduction of the legislation, low-skilled workers in NY decreased their share of remote work paid days relative to those in other states. In other words, a negative β_3 suggests an adverse effect of the legislation on the share of remote work paid days for low-skill workers in the treated state. Results reported in Table (4) shows that the effect is significant and negative also after controlling for observables, column (2), and beyond time, age, industry and state fixed effects, column (3). The effect estimated with the Diff-in-Diff provide additional and more robust evidence about the empirical prediction of the model, outlined in proposition 5. Furthermore, it addresses the concern that the estimates for β_7 in triple DiD are driven down by high-skill workers increasing

[28] Some controls are excluded with respect to the estimate of Equation (39), in order to preserve observations around the date of the treatment.

[29] Table 5 reports the results of estimating the same specification on a 24-months window, with 12 motnhs before and 12 months after the treatment.

	(1)	(2)
Dep. Var.	% remote work	% remote work
Treat	9.149***	
	(1.325)	
Post	0.682	
	(0.874)	
Treat $\times$ Post	-3.909***	-3.691***
	(0.874)	(0.869)
Constant	30.95***	38.61***
	(1.325)	(0.895)
Observations	20,643	20,643
R-squared	0.001	0.115
Controls	NO	YES
Fixed effects	NO	YES
Clust. errors	State-level	State-level

Table 4: Double DiD on low-skill workers (NY vs the rest of US). The estimation is performed in a 12-months window, 6 months before and after the treatment. Controls include the log of income and a dummy for gender. Fixed effects include age, time, industry, and state. Continuous variables are normalized to mean zero. Robust errors are clustered at the state level and reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

their share of remote work, since that specification does not account for trending differences between (skill) groups. It proves that a reduction in the effectiveness of monitoring causes low-productivity workers to work at the business premises, thereby reducing their average share of remote work days over total working days. In other words, restrictive regulation on monitoring implies a reduction in the share of remote work days for low-skill workers.

B Summary Statistics

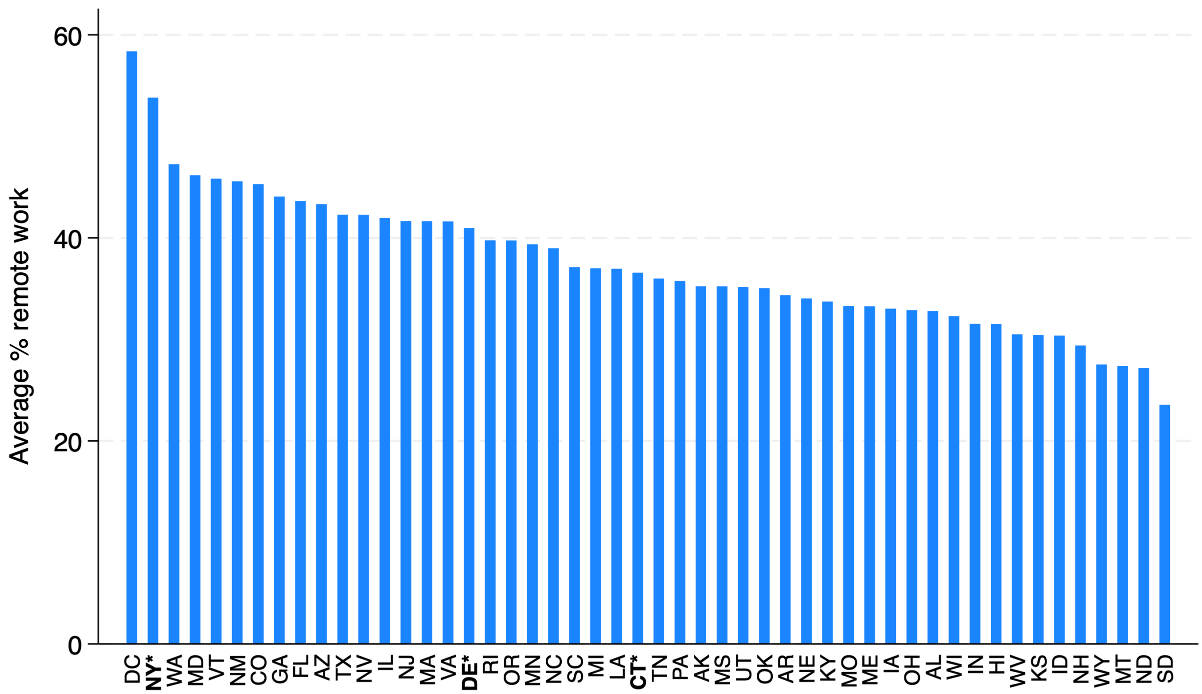

Figure B.2: Weighted average share of remote work days, by state. States highlighted in bold and with the asterisk are the 'treated' states, those with low-effectiveness of monitoring due to legislative restrictions.

	(1)	(2)
Dep. Var.	% remote work	% remote work
Treat	5.117***	
	(1.048)	
Post	-1.328**	
	(0.592)	
Treat × Post	-1.549**	-1.442***
	(0.592)	(0.526)
Constant	32.28***	37.37***
	(1.048)	(0.616)
Observations	42,363	42,363
R-squared	0.001	0.101
Controls	NO	YES
Fixed effects	NO	YES
Clust. errors	State-level	State-level

Table 5: Double DiD on low-skill workers (NY vs the rest of US). The estimation is performed in a 24-months window, 12 months before and after the treatment. Controls include the log of income and a dummy for gender. Fixed effects include age, time, industry, and state. Continuous variables are normalized to mean zero. Robust errors are clustered at the state level and reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 6: Summary Statistics about the sample employed for the pooled OLS

	Mean	SD	Min	Max	N
Remote work, %	41.75	45.65	0	100	82908
Less than high-school degree	28.16	41.87	0	100	1010
High-school degree	30.59	43.48	0	100	15256
1 to 3-years of college	36.84	45.14	0	100	18975
4-year college degree	50.44	45.42	0	100	24451
Graduate degree	55.05	44.53	0	100	23216
Years of Education	14.65	2.31	10	21	82908
2019 Earnings, $ Thousand	62.11	81.06	15	1000	82908
Age	41.64	11.55	25	57	82908
Children Y/N	0.45	0.50	0	1	82908

Table 7: Summary Statistics sample estimation in NY, Pre- and Post-Treament

	Mean	SD	N
Pre-Treatment			
Remote work, %	55.56	44.01	2173
Years of Education	15.68	2.45	2173
2019 Earnings, $ Thousand	92.21	113.39	2173
Age	41.85	10.18	2173
Post-Treatment			
Remote work, %	54.61	44.18	4729
Years of Education	15.86	2.38	4729
2019 Earnings, $ Thousand	96.27	131.47	4729
Age	41.06	9.95	4729
Total			
Remote work, %	54.89	44.13	6902
Years of Education	15.80	2.41	6902
2019 Earnings, $ Thousand	95.08	126.47	6902
Age	41.29	10.02	6902

Table 8: Summary Statistics sample estimation for the DiD, NY vs Rest of US

	Mean	SD	N
Rest of US			
Remote work, %	39.35	45.31	45775
Years of Education	14.60	2.32	45775
2019 Earnings, $ Thousand	61.72	81.65	45775
Age	42.41	11.53	45775
NY			
Remote work, %	54.89	44.13	6902
Years of Education	15.80	2.41	6902
2019 Earnings, $ Thousand	95.08	126.47	6902
Age	41.29	10.02	6902
Total			
Remote work, %	40.59	45.41	52677
Years of Education	14.70	2.35	52677
2019 Earnings, $ Thousand	64.39	86.57	52677
Age	42.32	11.42	52677

Table 9: Summary Statistics sample estimation for the DiD, rest of US pre- and post-

	Mean	SD	N
Pre-Treatment			
Remote work, %	39.10	45.50	14528
Years of Education	14.55	2.32	14528
2019 Earnings, $ Thousand	61.29	78.57	14528
Age	43.18	11.49	14528
Post-Treatment			
Remote work, %	39.47	45.22	31247
Years of Education	14.63	2.31	31247
2019 Earnings, $ Thousand	61.92	83.07	31247
Age	42.04	11.53	31247
Total			
Remote work, %	39.35	45.31	45775
Years of Education	14.60	2.32	45775
2019 Earnings, $ Thousand	61.72	81.65	45775
Age	42.41	11.53	45775