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SKILL-BIASED REMOTE WORK AND INCENTIVES

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Skill-biased remote work and incentives

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Abstract
We document four key trends since the pandemic: a surge in remote work, an increase in performance pay, their joint occurrence, and the skill-biased nature of this complementarity. We develop a firm-worker model that explains this evidence. We show that, under risk aversion, the incentive-compatible performance pay premium falls with worker's skills, as the likelihood of a good performance increases. Hence, the firm uses performance pay if the worker is sufficiently skilled and fixed pay with monitoring, otherwise. The unforeseen pandemic shock forces the firm to adopt remote work and reduces monitoring effectiveness. As a result, the firm relies more on performance pay. Post-pandemic, the firm always sticks to the remote work if the worker is sufficiently skilled. If the worker is too unskilled for performance pay to be cost-effective, the firm sticks to remote work only if remote monitoring is effective. Accordingly, the model predicts that a decline in remote monitoring efficacy could reduce remote work for less-skilled workers only. To test this, we exploit temporal variation in legislation in New York State, using a Difference-in-Differences approach, to estimate the impact of stricter regulations of remote monitoring on the adoption of remote work. Such a test strongly supports our model's predictions. Our findings suggest that pandemic policies and regulations may have played a significant role in shaping the adoption and persistence of remote work and performance pay.

Keywords: Remote Work, Performance Pay, Monitoring, Skills, Incentives.
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 systematically documented by Barrero et al. (2023), the incidence of remote working days increased from 7.2% in 2019 to 61.51% in 2020. Some of that change reversed as temporary pandemic-related restrictions were lifted. Still, as reported by the same authors, the incidence of remote work stands at 29% as of January 2025, suggesting that the pandemic triggered a structural change in the relevance of remote work. Using Lightcast data on US job postings, we document that performance pay has become an increasingly common element of the compensation schemes, alongside remote work, especially in high-skill occupations. We propose a model that rationalizes such a pattern and generates a testable prediction for which we find robust evidence.

We model a firm that operates over three periods and employs a one-period living worker in each period. The expected output depends on the workers' effort, which is non-contractible. Workers are endowed with a given skill level, which affects their productivity and, thereby, the likelihood of high output conditional on exerting high effort. The firm can incentivize workers through either a fixed salary with effort monitoring or performance pay. Additionally, it chooses between two business models: one in which workers operate from business premises (office model) and another where they works remotely (remote model). Each of the two models requires an implementation cost. The three periods correspond to the pre-pandemic, pandemic, and post-pandemic phases, with the pandemic modeled as an unforeseeable shock that temporarily prevents the firm from operating under the office-based business model.

The core mechanism driving the model's results rests on four realistic assumptions. First, workers are risk-averse.[1] Second, ceteris paribus, they prefer remote work over office work.[2] Third, monitoring worker's effort is less effective remotely than in the office. Intuitively, under remote work, firms lose access to some of the monitoring tools that are available on office premises.[3] Fourth, be-

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

[2]A substantial body of recent literature documents workers' significant willingness to pay for the option to work from home. A recent paper by Cullen et al. (2025) estimates that, on average, employees are willing to accept a 25% pay cut for partly or fully remote roles. See also Mas and Pallais (2017) and Maestas et al. (2023)

[3]Ko and Baek (2024) document how firms have introduced computer monitoring for telecommuting employees to address misreporting and noncompliance, suggesting that traditional monitoring mechanisms are less effective in

fore the pandemic, the firm adopts the office business model. This assumption is supported by the evidence discussed earlier, which shows that remote work was not common before the pandemic.

The main results of the model are as follows. First, regardless of the pandemic or the chosen business model, the firm adopts performance pay to incentivize a worker only if her skill level is sufficiently high. Otherwise, it opts for fixed pay with effort monitoring. Two opposing effects are at work. On the one hand, a higher level of worker's skills increases the probability that the worker performs well and the firm must pay the performance premium, raising the expected cost of performance pay. On the other hand, a more skilled worker requires a lower performance premium to exert effort, as she is more likely to earn it, thereby reducing the expected cost of performance pay. While both effects are always present, under risk aversion, the second effect dominates the first, making performance pay more cost-effective as the level of workers' skills increases.

Second, remote work persists after the pandemic. The pandemic forces the firm to adopt the remote model. Consequently, after the pandemic, the firm can freely switch between the two models, having already incurred the related implementation costs. Since workers prefer remote work, the remote model is economically preferable, and thus persists, provided that workers are sufficiently skilled for performance-based pay to be cost-effective. Conversely, if the worker is so unskilled that fixed pay with monitoring is the preferable incentive scheme, the firm sticks to the remote model only if remote monitoring is effective enough, and reverts to the office model otherwise.

Third, and relatedly, the reduced efficacy of remote monitoring compared to office-based monitoring implies that under the remote model, performance pay is used for a wider range of skill levels. Fourth, and as a consequence, remote work and performance pay are inherently linked and skill-biased.

Crucially, our model predicts that if the firm's ability to monitor worker effort remotely becomes sufficiently ineffective, a decline in remote work among low-skilled workers should be observed. To test such a prediction, we exploit variation in remote monitoring regulations in New York State over time, using a Difference-in-Differences (DiD) approach and data from the Survey of Working Arrangements and Attitudes (SWAA) by Barrero et al. (2021). First, we evaluate the model on

remote settings.

a sub-sample of non-college (low-education) workers, comparing those in New York to workers in control-group states, and find a significant negative effect on their relative share of remote workdays. Next, we estimate the same specification for college-educated workers and find no effect. The empirical findings are consistent across alternative specifications. Under the tenable assumptions that: (i) more restrictive regulations reduce the effectiveness of remote effort monitoring, and; (ii) education serves as a proxy for skills, these results provide robust support for the model's predictions.

Notably, our analysis provides indirect support for the idea that firms' need to incentivize workers, either by monitoring their effort or measuring their performance, plays a crucial role in shaping remote work strategies.

Regarding remote monitoring, Ko and Baek (2024) provide evidence that the implementation of computer monitoring technologies significantly enhances firm productivity and reduces employee noncompliance. This finding substantiates the idea that the adoption of remote monitoring technologies, accelerated by the pandemic, has played a pivotal role in the diffusion and persistence of remote work. At the same time, it suggests that a decline in the effectiveness of these technologies, due, for instance, to the introduction of tighter privacy laws or other regulations, could lead to substantial productivity losses. Consequently, firms might reconsider remote work for employees subject to monitoring and revert to office-based arrangements. This is precisely what our model predicts and what we observe in the data.

Similarly, our model suggests that remote work is more likely to be adopted by firms capable of generating reliable measures of workers' output, which are necessary to implement performance pay schemes. This aligns with the empirical findings of Lamorgese et al. (2024), who analyze firm survey data and show that companies with structured managerial practices, specifically, those relying on formalized procedures for setting targets and monitoring outcomes, were better positioned to transition abruptly and extensively to remote work at the onset of the pandemic.

Finally, the substantial impact of these regulations on firms' choices regarding business models and incentive schemes suggests they may have significant aggregate effects on remote work, helping to explain the cross-regional differences documented in the literature (Aksoy et al., 2022; Zarate et al., 2024).

This paper contributes to two strands of literature and builds a bridge between them. First, it adds to the extensive literature on the provision of incentives in the workplace, surveyed by Lazear (2018), by examining how workers' skills and productivity shape the interplay between the firm's choices of performance vs. fixed pay and remote vs. office business models. The positive impact of performance pay on productivity is analyzed in the landmark studies of Lazear (1986) and Lazear (2000). In the latter, this effect is found to be equally driven by the average worker exerting more effort and by the firm's ability to hire more skilled - and therefore more productive - employees. Our model introduces a novel channel, based on worker's risk-aversion, to explain the observed link between workers' level of skills, performance-pay contracts, and remote work. More closely related to our paper, Bandiera et al. (2015) develop a model in which heterogeneous firms and managers match through their choice of incentive policies, which they test using a purpose-built survey. They find that more talented and risk-tolerant managers are matched with firms offering steeper performance-based contracts. Similarly, a key result of our model is that, under workers' risk aversion, the expected cost of a performance-pay incentive scheme declines with workers' skill, which makes performance pay, and remote work, more attractive for the firm.

Second, our analysis adds to the fast-growing literature on the causes and consequences of the rise and persistence of remote work. Barrero et al. (2021) develop a model to explain why remote work was not widely adopted before the pandemic and why it is likely to persist post-pandemic. Their mechanism, related to ours –albeit different– relies on firms' imperfect understanding of remote work until the pandemic forced them to adopt it. They also provide extensive evidence on the surge of remote work and its persistence, highlighting considerable investments in physical, human, and organizational capital - key elements in our model's mechanism. Similarly, Bick et al. (2023) document the increase and persistence of remote work, arguing that the pandemic may have permanently altered workers' commuting choices, thereby sustaining remote work arrangements. Hsu and Tambe (2025) show that offering remote work attracts more experienced and diverse job applicants, with an estimated wage premium of about 7% of posted salaries. Our paper provides an alternative explanation for the observed skill bias in remote work.

The structure of the paper is the following. Section 2 describes the evidence that motivates our analysis. Section 3 presents the model. Section 4 derives the optimal incentive schemes. Section 5 characterizes the firm's behavior before, during, and after the pandemic. It derives the main results, discusses how they help rationalizing the observed empirical patterns and derives the key empirical prediction specifically tied to the model, as discussed above. Section 6 presents the empirical analysis aimed to test for such a prediction. Section 7 concludes.

2 Motivating evidence

Using a comprehensive dataset of U.S. job postings provided by Lightcast, spanning from 2018 to 2023, we describe the evolution of the demand for jobs offering remote work and performance-based compensation. To single out vacancies offering remote work, whether fully remote or hybrid, we adopt the methodology of Hansen et al. (2023).[4] To identify vacancies offering performance-based compensation, we tokenize and clean the text of more than 230 million postings, removing stopwords and extracting bigrams and trigrams containing terms related to compensation and performance.[5]

Figure 1 shows two significant structural effects associated with the pandemic. The pandemic prompted a significant shift in the remote work trend. Before 2020, remote work accounted for only about 2% of jobs. With the onset of the pandemic, this share tripled to nearly 6% by early 2020 and continued to rise steadily until 2023. The intensity of remote work varies across occupations and industries, with technology and administrative roles exhibiting the highest prevalence, while physically-intensive jobs, such as those in transportation and hospitality, lag behind. Moreover, with the pandemic, the share performance-pay jobs also increased, albeit more gradually. Stable before the pandemic, the prevalence of performance pay reached almost 10% by 2024. Occupations

[4] Hansen et al. (2023) employ a human-trained machine learning algorithm, i.e. the Working-from-Home Algorithmic Measure (WHAM) model, to predict whether a job posting involves some form of remote work. This approach maximizes accuracy, achieving a rate of approximately 99%, while effectively minimizing false positives. Notably, in the post-pandemic period, employers have increasingly made explicit in job postings when remote work is not permitted for a given position.

[5] Specifically, we focus on bigrams and trigrams that pair terms such as 'bonus', 'commission', 'salary', or 'pay' with words like 'performance', 'productivity', or 'incentive'. We deliberately exclude combinations referring to payments linked to experience, sign-on bonuses, or relocation bonuses. While dictionary-based methods may raise concerns regarding potential fragility, we believe the identification of performance pay is less susceptible to time-varying biases. Unlike for remote work, whose practices shifted significantly after the pandemic when employers started to specify 'remote work is not allowed' or 'no remote work', the interpretation of performance pay terms has remained more stable in this regard.

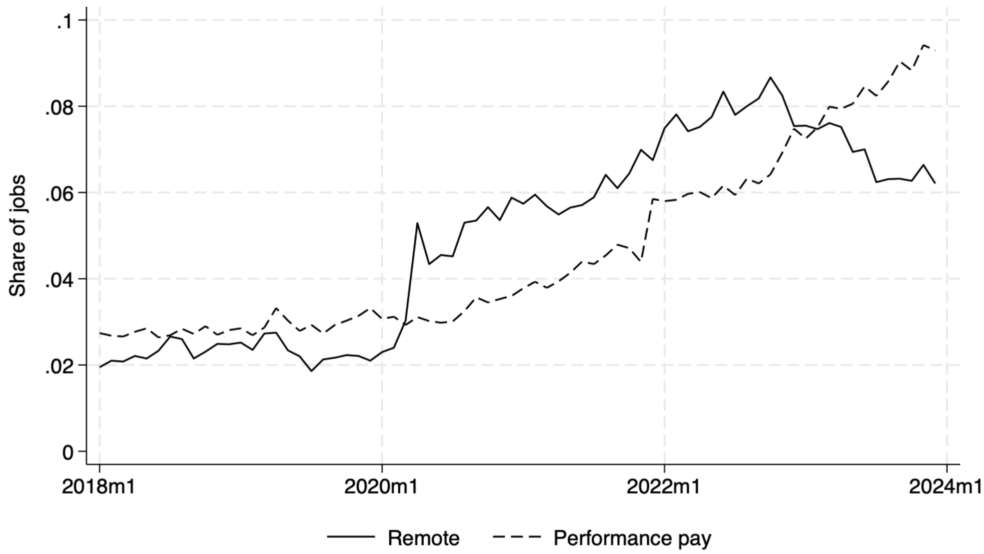


Figure 1: Monthly share of remote and performance-pay jobs, from 2018 to 2023.

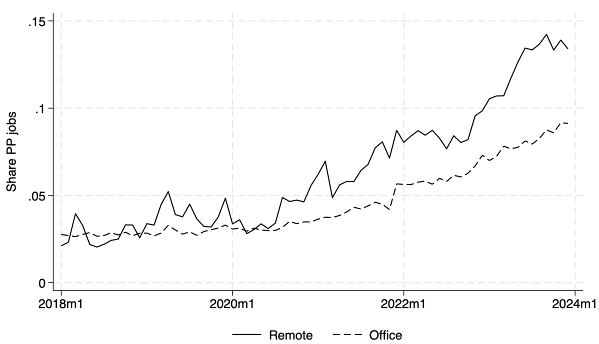
such as sales, finance, and construction exhibit the highest levels of performance pay, reflecting the incentive structures commonly used in those fields.

2.1 The complementarity between remote work and performance pay

An analysis of the share of performance pay across remote and office jobs, as depicted in panel (a) of Figure 2, suggests that firms increasingly linked compensation to performance in association with remote work. With the onset of the pandemic, the share of performance pay increased more significantly for vacancies offering remote work than for those offering office-based work, with the divergence between the two trends widening over time. We further explore the relationship between remote work and performance pay at the occupational level by computing the shares of job types within each of the most detailed O*NET-SOC 2019 occupational codes and restricting the analysis to those jobs that can be performed at home, as identified by Dingel and Neiman (2020).[6] Panel (b) of figure 2 further shows the complementarity at the occupation level, for the post-pandemic period. The shares of vacancies offering remote work and performance-pay respectively, are positively correlated also considering such aggregation. After the pandemic, five major occupational

[6] Graphs look similar also by including all occupations, showing always a positive relationship between the shares of vacancies with remote work and performance-pay respectively, at the occupational level.

groups, that represent 35% of total vacancies, account for more than 75% of vacancies offering remote work and performance pay. These groups are: management (11-0000), business and financial operations (13-0000), computer and mathematical (15-0000), sales and related (41-0000), office and administrative support (43-0000). In particular, the following finest occupations, that constitute 8% of total jobs, account for more than 25%: marketing managers (11-2021.00), sales managers (11-2022.00), management analysts (13-1111.00), software developers (15-1252.00), insurance sales agents (41-3021.00), sales representatives (41-4012.00), and customer service representatives (43-4051.00).



(a) Performance-pay across remote and office jobs

(b) Shares across occupations, 2020-2023

Figure 2: The complementarity between remote and performance pay. Panel (a) reports the monthly share of jobs that include performance pay as a compensation scheme among remote and office positions. Panel (b) shows the relationship at the occupation level, restricting to those occupations that can be performed at home according to Dingel and Neiman (2020). Each circle represents an occupation, where its size is proportional to the number of jobs over the post-pandemic period.

To investigate the hypothesis that remote work and performance pay move together, we exploit the granularity of the data and examine the correlation between the two phenomena at vacancy level. In particular, we estimate

$$PP_i = \alpha + \beta R_i + \mu_i \tag{1}$$

where α is a constant, PP_i is a dummy equal to 1 if vacancy i includes some form of performance-based compensation, R_i is a dummy equal to 1 if vacancy i offers the remote work option, and μ_i is an error term. The results, reported in table 1, offer support to the idea of a strong complementarity between the two vacancy's features. As we are interested in estimating the differential probability of observing performance pay across remote and office positions for otherwise identical jobs, we include a rich set of fixed effects that isolate the within job variation. This is crucial to ensure that results are not driven by variation across different periods, cities, firms, occupations, or industries. The results show that the probability of observing performance pay increases by around 1/3 and establishes at almost 7.5% for remote jobs.

Dep. Var.	Performance Pay
Remote	0.0174***
	(0.0001)
Constant	0.0567***
	(0.0000)
Observations	155,349,876
R-squared	0.2776
Fixed Effects	✓

Table 1: The complementarity between remote work and performance pay. The period considered start since the pandemic onset, from April 2020 to 2023. Fixed effects include month, city-level location, firm, occupation (O*NET-SOC 2019) and industry (2-digit NAICS). Standard errors are reported in parenthesis (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

2.2 Skill-biased remote work and performance pay

In this subsection, we explore the correlation between the skill content of a vacancy and its likelihood of offering the remote work option and performance-based pay. To assign a skill level to a vacancy, we rely on the occupation code associated to that vacancy. The dataset comes with occupation codes based on the O*NET-SOC 2019 classification. Using a series of crosswalks we retrieve the same harmonized classification used in Autor and Dorn (2013).[7] A vacancy is assigned a high-skill content if it is associated with a high-skill occupation as defined in Cerina et al. (2023).[8] Otherwise, we assign the vacancy a low-skill content.

To quantify the differential probability of observing remote work across different skill contents,

[7]We applied the crosswalks to go from the O*NET-SOC 2019 to O*NET-SOC 2010 to CENSUS 2010 and finally to the Autor and Dorn (2013) classification. In the end, we are able to match 95% of occupation codes, excluding agriculture and military. Including those, the match rises up to 96%.

[8]Specifically, we define as high-skilled all ”managerial and professional specialty occupations” (1990 CENSUS codes 003-200).

we estimate the following model

$$R_i = \alpha + HS_i + \mu_i \tag{2}$$

where R_i is a dummy equal to 1 if vacancy i offers remote work, α is a constant, HS_i is a dummy equal to 1 if the vacancy i is associated to an occupation classified as high-skill, and μ_i is an error term. To assess whether the probability of observing performance pay varies with the skill content of a vacancy we estimate a model equivalent to (2) in which the dependent variable would take value 1 if the vacancy offers performance-based pay and zero otherwise.

Table 2 reports the results obtained by estimating the above models with remote work and performance pay as dependent variables, using a sample covering the period from March 2020 to 2023. The results indicate that vacancies with high skill content are more likely to offer the remote work option and performance-based compensation. As for the estimates related to complementarity, fixed effects are crucial to isolate the variation across skill levels from that across different periods, cities, firms, and industries. Results show that the skill content of jobs remains significantly associated with a positive sign to remote work and performance pay even after controlling for such a rich set of fixed effects. In particular, the probability of observing remote work and performance pay increases with the skill content of a vacancy by 56% and 11%, respectively.

Dep. Var.	Remote	Performance Pay
High-skilled occ.	0.0278***	0.0062***
	(0.0000)	(0.0001)
Constant	0.0495***	0.0554***
	(0.0000)	(0.0000)
Observations	147,086,059	147,086,059
R-squared	0.2833	0.2711
Fixed Effects	✓	✓

Table 2: The composition of remote and performance pay across skill. The estimation is performed from March 2020 to 2023, since the start of the pandemic. Fixed effects include month, city-level location, firm and industry (2-digit NAICS). Standard errors are reported in parenthesis (*** p<0.01, ** p<0.05, * p<0.1).

3 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 period, the firm operates a production process that requires one unit of worker's labor and delivers an output,

$$Y = \begin{cases} Y_H > 0 & \text{with probability } p_e \\ 0 & \text{with probability } 1 - p_e \end{cases} \tag{3}$$

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 $e \in \{e_L, e_H\}$. We assume that if the firm does not produce in one period it goes permanently out of business.

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.

First-time adoption of the business model $i = O, R$ requires a one-time fixed implementation cost, C_i, which has a broad interpretation.[9] 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 cost of uncertainty about the effectiveness of the business model and a cultural cost 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 limited adoption. The culture cost depends on how typical or traditional a business model is given the prevailing business culture. Clearly, this cost can also 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 will assume that, in period 0, before the pandemic shock, $C_O < C_R$ holds in

[9] For simplicity, we assume that the investment associated with the implementation cost does not depreciate over time. The results of our analysis hold true in the case of positive depreciation if not too fast.

such a way that, in the absence of a pandemic, the firm prefers to implement the O model rather than the R one.[10] Indeed, the limited adoption of the R model before the pandemic suggests the dominant culture is the O model so that in period 0 the firm faces substantially more uncertainty about the viability and efficacy of the R model compared to the O one. 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 well established and therefore more predictable.[11] One could argue that the firm could resolve the uncertainty associated with the R model through experimentation. However, this would require substantial material and immaterial investments, which feeds into the implementation cost of that model.[12]

Each of the three workers has an endowment of one unit of labor, a level of skills, $s \in (\underline{s}, \overline{s})$, and preferences described by the following utility function

$$u(c, e) = \alpha_i f(c) - g(e) \tag{4}$$

where $\alpha_i f(c)$ and $g(e)$ measure utility from consumption, c, and disutility from effort, e, respectively, with $f'(c) > 0$, and $g'(e) > 0$, while 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 ($i = O$). Specifically, we assume $\alpha_R > \alpha_O \equiv 1$ to capture, in a reduced form, the idea that remote work enhances the utility derived from consumption - potentially due to greater time flexibility. Empirical evidence supports this assumption: Aksoy et al. (2023) show that 34% of commuting time saved through remote work is reallocated to leisure, while 11% is dedicated to caregiving activities.[13]

[10] See Proposition 3.

[11] A similar argument is put forward by (Barrero et al., 2021).

[12] Typical examples of the 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 personnel training 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.

[13] An alternative, yet equivalent modeling strategy, would be to assume $u(c, e) = f(c) - \alpha_i g(e)$, with $\alpha_R < \alpha_O \equiv 1$, to capture the idea that effort is less burdensome when exerted from home. Both views are consistent with the idea

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.

3.1 Information asymmetries

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 alternative 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 firm can monitor workers only by means of techniques that are feasible at distance. In other words, remote work renders all the on-site monitoring techniques used at business premises unfeasible. Differently, when workers are on business premises, the firm can adopt both on-site and remote monitoring techniques. Accordingly, we assume $\theta_O > \theta_R$.

The other technology allows the firm to observe the early advancement of the production process at an interim date.[14] Specifically, the firm can observe an early signal, $\rho = \{L, H\}$, with H(high) $>$ L(low), about the advancement of the production process. We let the probability of the signal ρ, $\sigma_{\rho,e} \in (0, 1)$, depend on the worker's effort, e, such that the probability of observing a signal H (L) is higher (lower) when the worker's effort is H (L), i.e. $\sigma_{H,H} > \sigma_{H,L}$, which implies $\sigma_{L,H} < \sigma_{L,L}$, given $\sigma_{L,e} + \sigma_{H,e} = 1$.[15] Specifically, we assume $\sigma_{H,L} \equiv \beta\sigma_{H,H}$, with $\beta \in (0, 1)$. Based on the signal, ρ, the conditional probability of success of the firm's project is v_ρ, with $v_H > v_L$.

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

that, ceteris paribus, workers prefer remote work over office work (see Cullen et al. (2025) and Maestas et al. (2023) among the others).

[14] In principle, one could extend our framework to assume that information acquisition, whether about effort or advancements in the production process, is costly. In practice, including such costs does not provide any additional relevant insight.

[15] Note that this specification preserves the property that the signal is never perfectly informative about the level of effort exerted by the worker.

production process is

$$p_e = \sigma_{H,e} v_H + (1 - \sigma_{H,e}) v_L \tag{5}$$

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 prior probability of success of the project, p_e. We find it natural the following

Assumption 1. *The probability of observing a high signal about the prospects of the firm is increasing in the worker's skills, that is $\sigma_{H,e} = \sigma_{H,e}(s)$ with, $\sigma'_{H,e}(s) > 0$. With no loss of generality, we also impose, $\lim_{s \to \overline{s}} \sigma_{H,H}(s) = 1$, and $\lim_{s \to \underline{s}} \sigma_{H,H}(s) = 0$.*

The idea is that, for a given task, the effectiveness of the worker's contribution positively depends on her ability. A competent software developer is likely to have a higher positive impact on the firm's prospects than an incompetent one. As for the second part of the assumption, it states that the probability of observing a high signal in case of high effort tends to one if the worker's skills are very high, while such a probability tends to zero if they are very low. Correspondingly, when exerting low effort, the probability of observing a high signal converges to $\beta < 1$ for a very high-skilled worker and to zero for a very low-skilled worker.

3.2 Workers' skills and productivity

Based on equation (5), in each period, the expression of the gross expected product generated by the firm is

$$E(Y|e) = [\sigma_{H,e}(s)(v_H - v_L) + v_L] Y \tag{6}$$

so that the expected impact of the worker's effort is

$$E(Y|H) - E(Y|L) = (1 - \beta)\sigma_{H,H}(s)[v_H - v_L] Y \tag{7}$$

The above measure of worker's productivity depends on two parts: 1) $[v_H - v_L]Y$, which relates to the characteristics of the production process, and; 2) $(1 - \beta)\sigma_{H,H}(s)$, which measures the impact of the worker's effort on the probability of observing a favorable signal about the prospects of production. Note that the worker's productivity depends positively on the worker's skills, s, since we assume that $\sigma_{H,H}(s)$ is increasing in s. This is consistent with the idea that skilled workers are more involved in tasks crucial for the outcome of the firm's production process compared to unskilled ones. For example, a software developer is likely to be more crucial for the success of an ICT than one of the many operators of the firm's customer care center. Likewise, a competent developer is likely to have a higher positive impact than an incompetent one.

3.3 Timing

In period 0, the economy operates under normal conditions and both business models are suitable options. In period 1, a one-period pandemic shock hits the economy that prevents the firm from operating under model O in that period. The pandemic shock is modeled as an unforeseeable event characterized by zero probability. Consequently, in period 0, the firm assigns no value to the choice of paying the one-time fixed implementation cost associated with model R to be able to operate in period 1 in the event of a pandemic shock. That follows because there are no foreseeable benefits of organizing the firm to deal with future pandemic shocks.[16] In period 2, the pandemic event ends, and the economy returns to normal. The time structure of the pandemic shock is common knowledge.

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

i. Having observed whether a pandemic shock occurred or not, the firm chooses the organizational model(s) and makes a take or leave offer to the worker;

ii. The worker decides whether to accept or reject;

iii. Production takes place, and payoffs are realized and distributed.

4 Optimal incentive schemes

Given the available information acquisition technologies, there are two alternative ways in which the firm can provide the worker with the incentive to exert high effort. One possibility is to monitor

[16] It is easy to show that model's results hold true in the more general case of a positive probability of a pandemic shock, provided that such a probability is low enough. Modeling the shock as a zero probability event streamlines the exposition by avoiding the unnecessary complication of going through the analysis of how the strategy of the firm might change depending on the probability of the shock.

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, with $i = O, R$. We refer to this as the incentive scheme 'F'. Alternatively, the firm can choose to observe 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 project's advancement so that a high signal is informative of the worker's effort. We label 'P' such a performance pay scheme.

In this section, we characterize the two alternative optimal incentive schemes the firm could use to incentivize the worker conditional on the organizational model, $i = O, R$, adopted by the firm.

4.1 Optimal incentive scheme F

In any period, the wage schedule $w_{F,i}$ associated with the F scheme, should satisfy the following incentive compatibility constraint (ICC) and participation constraint (PC):

$$\text{ICC}: \quad \alpha_i f(w_{F,i}) - g(e_H) \geq (1-\theta_i)\alpha_i f(w_{F,i}) - g(e_L) \tag{8}$$

$$\text{PC}: \quad \alpha_i f(w_{F,i}) - g(e_H) \geq 0 \tag{9}$$

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 is normalized to zero. It is immediate to verify that the wage schedule associated with the optimal incentive scheme F satisfies

$$f(w_{F,i}) = \max\left(\frac{g(e_H) - g(e_L)}{\theta_i \alpha_i}, \frac{g(e_H)}{\alpha_i}\right) \tag{10}$$

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 2.

$$\theta_i < 1 - \frac{g(e_L)}{g(e_H)} \tag{11}$$

Given (10) and Assumption 2,

$$w_{F,i} = f^{-1}\left(\frac{g(e_H) - g(e_L)}{\alpha_i \theta_i}\right) \tag{12}$$

Note that since $f(\cdot)$ is a monotonically increasing function, $f^{-1}(\cdot)$ is also monotonic and increasing in its argument. Accordingly, $w_{F,i}$ decreases in the monitoring effectiveness, θ_i. The higher the monitoring effectiveness, the more powerful the incentive scheme F, which implies that the firm could set a lower wage, $w_{F,i}$. Moreover, $w_{F,i}$ is decreasing in α_i. The incentive-compatible fixed wage decreases the higher is the utility of a given level of consumption. Finally, $w_{F,i}$ increases with $g(e_H) - g(e_L)$. The incentive compatible fixed wage increases with the worker's benefits from shirking.

4.2 Optimal incentive scheme P

Under the incentive scheme P, the wage schedule takes the form of a lottery,

$$\omega_i(s) = [w_{H,i} \circ \sigma_{H,H}(s); w_{L,i} \circ (1 - \sigma_{H,H}(s))] \tag{13}$$

which depends on skills through the probability of observing a high signal, $\sigma_{H,H}(s)$. The lottery must satisfy the following incentive compatibility (ICC) and participation constraints (PC):

$$ICC \; : \; \alpha_i[\sigma_{H,H} f(w_{H,i}) + \sigma_{L,H} f(w_{L,i})] - g(e_H) \geq \alpha_i[\sigma_{H,L} f(w_{H,i}) + \sigma_{L,L} f(w_{L,i})] - g(e_L) \tag{14}$$

$$PC \; : \; \alpha_i[\sigma_{H,H} f(w_{H,i}) + \sigma_{L,H} f(w_{L,i})] - g(e_H) \geq 0 \tag{15}$$

where, to simplify notation, from now on, we write the function $\sigma_{H,H}(s)$ simply as $\sigma_{H,H}$. As in the incentive scheme F, the ICC (14) states that the expected utility from exerting high effort should exceed the expected utility of shirking. The PC (15) states that the expected utility from participation should exceed the utility associated with the outside option. It is immediate to verify that the optimal incentive scheme P is such that the ICC and the PC hold as strict equalities. Accordingly, the optimal values of $w_{H,i}$ and $w_{L,i}$ solve the following system of simultaneous equations:

$$f(w_{H,i}) - f(w_{L,i}) = \frac{g(e_H) - g(e_L)}{\alpha_i(1-\beta)\sigma_{H,H}} \tag{16}$$

$$\sigma_{H,H} f(w_{H,i}) + (1-\sigma_{H,H}) f(w_{L,i}) = \frac{g(e_H)}{\alpha_i} \tag{17}$$

Importantly, (16) implies that the performance utility premium - $f(w_{H,i}) - f(w_{L,i})$ - is decreasing in worker's skills through the term $\sigma_{H,H}$. Being more productive, a more skilled worker requires a lower performance utility premium to exert high effort relative to a less skilled one: by exerting high effort, a more skilled worker is more likely to get the premium than the less skilled one, which increases the expected rewards from effort. Combining (16) and (17) yields

$$w_{L,i} = f^{-1}\left(\frac{g(e_L) - \beta g(e_H)}{\alpha_i(1-\beta)}\right) \tag{18}$$

$$w_{H,i} = f^{-1}\left(\frac{(1-\sigma_{H,H}\beta)\, g(e_H) - (1-\sigma_{H,H})\, g(e_L)}{\alpha_i\,(1-\beta)\,\sigma_{H,H}}\right) \tag{19}$$

Where it is immediate to verify that $w_{H,i} > w_{L,i}$ given $g'(e) > 0$. The following result holds

Proposition 1. *The expected wage that the firm pays under performance pay,*

$$E(\omega_i) = w_{L,i} + \sigma_{H,H}[w_{H,i} - w_{L,i}] \tag{20}$$

where $w_{L,i}$ and $w_{H,i}$ are given by (18) and (19), is strictly decreasing in the worker's level of skills, s, if and only if the worker is risk-averse; strictly increasing if and only if the worker is risk-lover, and constant if and only if the worker is risk-neutral.

Proof. See appendix.

Proposition 1 states a a crucial result of the model. It says that, if the worker is risk-averse, the incentive scheme P becomes less costly for the firm as the worker's level of skills, s, increases. The mechanism underlying such a result relies on the interplay of two opposing effects. On the one hand, the probability $\sigma_{H,H}$ that the firm has to pay the performance premium increases in skills s, which rises the expected cost of the incentive scheme P. On the other hand, the firm can pay a lower performance premium to a more skilled worker as she is more likely to get the premium, which reduces the expected cost of the incentive scheme P. While these two effects are at work irrespective of worker's risk attitude, under risk aversion the second one always dominates the first. In the rest of the paper, consistent with Chetty (2006) and Cohen and Einav (2007), we assume the worker is risk-averse and therefore has a utility function that is strictly concave in c. Formally, we adopt the following

Assumption 3. *The function $f(c)$ is homogenous of degree $\gamma < 1$, $f(c) = c^{\gamma}$.*

5 Firm's behavior

In each period, the firm chooses whether to produce or go permanently out of business, and, if producing, the business model, $i = O, R$, and the worker's incentive scheme, $j = F, P$, to adopt. In period 0, to implement any business model, the firm must incur the one-time fixed cost. Differently, in the following periods, it can either stick to the "inherited" business model or switch to a new model. Only in the latter case it would have to incur an additional implementation fixed cost.

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

In each period, for a given business model $i = O, R$, the firm decides which optimal incentive scheme to adopt if producing. Importantly, firm's expected revenues, which are equal to $p_H Y$ per period, do not depend on the adoption of the optimal incentive scheme. Moreover, there is no relationship between the fixed cost of implementing any business model and the cost of incentivizing the worker. Thereby, the only relevant dimension when choosing the incentive scheme is the related labor cost. In other words, in each period, the choice of the optimal incentive scheme is the one that minimizes the expected wage that the firm has to pay in that period. Such expected wage is given by (12) for the scheme F, and by (20) for the scheme P. The following result holds

Proposition 2. *Performance pay is skill-biased. For any given business model $i = O, R$, there always exists a unique threshold value,*

$$\widehat{s}_i : E(\omega_i(s)) \equiv w_{F,i} \tag{21}$$

of the worker's skills, s, such that the firm chooses the scheme P, if $s \geq \widehat{s}_i$, and the scheme F otherwise.

Proof. See appendix.

The above Proposition presents a key result. It says that, for a given business model, the firm's choice of incentive scheme varies with the worker's skills. As stated by Proposition 1, under risk aversion, the expected cost of the incentive scheme P monotonically falls with the worker's skills. Under assumption 3, the expected cost of P becomes infinitely large as skills tend to the lower bound. By contrast, under assumption 2, when skills are large enough, the expected cost of P becomes lower than the cost of F, which does not depend on skills. Accordingly, Proposition 2 follows. The intuition is that skilled workers, being more productive, are more likely to get the performance premium which implies that, if they are risk-averse, they can be more conveniently incentivized under scheme P rather than F. The model's property that performance pay is skill-biased helps explain the evidence in Section 2, showing that performance pay is more common in high-skill vacancies, as well as the extensive literature indicating that more skilled workers have a stronger preference for performance-pay contracts than less skilled ones.[17]

Importantly, Proposition 2 leads to the following

Corollary 1. *The threshold value of the worker's skills $\widehat{s}_i$ above (below) which the firm chooses incentive scheme P (F) under business model $i = O, R$ is strictly lower when the worker works remotely than at the business premises, i.e., $\widehat{s}_R < \widehat{s}_O$.*

Proof. See appendix.

The above corollary says that performance pay, when feasible, is optimal for a wider range of the worker's level of skills under the remote business model than under the office one. As the efficacy of remote monitoring is lower than office monitoring, under the R model, performance pay becomes a more effective incentive mechanism than fixed pay with monitoring. A further implication of this result is that, in the case of a worker with an intermediate level of skill, $s \in [\widehat{s}_R, \widehat{s}_O)$, the firms adopts the incentive scheme P under the R model and the incentive scheme F under the O

[17] See for instance (Eriksson and Villeval, 2008; Ewing, 1996; Lazear, 2000).

model. In other words, while according to Proposition 2, performance pay is skill-biased under both business models, corollary 1 indicates that it is less skill-biased under the R one.

5.2 Firm's decision to produce and the choice of the business model

The previous subsection shows that irrespective of the business model adopted by the firm, given the worker's level of skills, s, there is only one incentive scheme strictly preferred by the firm.

Regarding the choice of the business model, we make two important preliminary observations. First, since the firm can use only one business model at a time and it decides which business model to adopt after observing whether the pandemic shock occurred or not, it is always optimal for the firm to incur the fixed implementation cost for at most one business model per period.

Second, given that the worker prefers working remotely, $\alpha_R > \alpha_O \equiv 1$, the optimal incentive scheme under the O model could be characterized by a higher expected wage than under the R one.[18] Accordingly, when deciding which business model to implement in period 0, the firm considers that the O model might imply higher costs in terms of wages compared to R.

Based on such premises, in what follows we characterize the firm's production decision and the choice of the business model to adopt in each period.

5.2.1 Period 0: Pre-pandemic

We can state the following

Proposition 3. *In period* 0*, the firm chooses the business model* O *if the fixed implementation cost,* C_R*, associated with the first-time adoption of the business model* R*, is high enough to satisfy the following condition:*

$$C_O + 3\min(E(\omega_O), w_{F,O}) \leq C_R + 3\min(E(\omega_R), w_{F,R})] \tag{22}$$

and decides to produce if and only if

$$C_O + 3[\min(E(\omega_O), w_{F,O})] \leq 3p_H Y \tag{23}$$

[18]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.

and and adopts the incentive scheme F if the worker's skills, s, are such that $s < \widehat{s}_O$ and the scheme P if the reverse inequality holds.

Proof. See appendix.

The above proposition identifies the sufficient condition for the firm to adopt the O business model in period 0 and the necessary and sufficient condition for the firm to decide to produce, under the simplifying assumption that the intertemporal discount factor equals 1.[19] Intuitively, condition (22) states that the difference in the one-time fixed implementation cost between the R and the O business models, $C_R - C_O$, should be large enough and, in particular, larger than 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, $3[\min(E(\omega_O), w_{F,O}) - \min(E(\omega_R), w_{F,R})]$. The assumption that the pandemic shock is unforeseen shapes the result. If the probability of such a shock were non-negligible, when deciding the business model in period 0, the firm would also consider that by adopting the R model it would be able to operate in period 1 in the event of the pandemic without incurring any further fixed implementation costs. It then follows that, with a non-negligible probability of the pandemic shock, the condition for the firm to choose model O in period 0, and for the main results of our analysis to go through, would be more stringent than (22).

If condition (22) holds, choosing the O model and sticking to it is the optimal decision. Then, condition (23) simply says that in that case, producing is convenient if and only if the total expected cost is less than the total expected revenues over three periods.

Figure 3 illustrates the optimal strategy of the firm in period 0 as a function of the worker's skills, s, when condition (22) holds, so that the business model O dominates R irrespective of the incentive scheme. The red and black lines portray the choices of implementing the R or the O model in period 0, respectively, sticking to the adopted model in all subsequent periods. The straight and curve lines refer to the cases in which the firm adopts the F or the P wage scheme, respectively. The bold line is the locus of the minimal total cost the firm achieves for any level of the worker's skills. It shows that the optimal strategy is to always adopt model O, while choosing the F scheme

[19] Generalizing to the case of a positive interest rate does not change the essence of the results and complicates the notation.

for worker's skills below $\widehat{s}_O$ and the P scheme otherwise.[20] The situation described in Figure 3 is representative of real-world economies before the pandemic, in that remote work was not yet widespread.

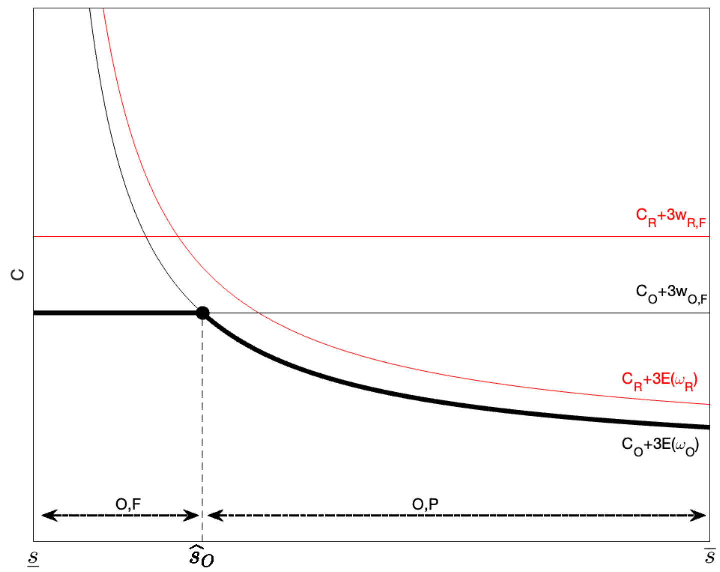


Figure 3: The red and black lines represent the total costs (implementation and labor) when the firm operates the R and the O models, respectively. The thick line represents the total cost associated with the firm's optimal strategy at $t = 0$ as a function of the worker's skills, s, when condition (22) holds.

5.2.2 Period 1: The pandemic

We now turn to the analysis of the effects of the pandemic, assuming that condition (22) holds so that in period 0, the firm implements the O business model. At the beginning of period 1, the pandemic shock occurs, which prevents the firm from continuing to operate under that business model. Under these circumstances, to avoid going out of business, the firm has to implement the R business model by incurring the implementation cost C_R. The optimal behavior of the firm is as follows.

[20]For simplicity, in the graph, we represent a special case in which the level of skills is the same for the three workers hired in the three periods. We adopt the same approach in all subsequent graphical representations.

Proposition 4. *In period* 1*, during the pandemic, the firm decides to produce if and only if*

$$C_R + \min\left(w_{F,R}; E(\omega_R)\right) + \min\left(\min\left(w_{F,O}; E(\omega_O)\right), \min\left(w_{F,R}; E(\omega_R)\right)\right) < 2p_H Y \tag{24}$$

and adopts the incentive scheme F if the worker's skills, s, are such that $s < \widehat{s}_R$ and the scheme P if the reverse inequality holds.

Proof. See appendix.

Condition (24) involves the expected revenues and the expected labor costs of periods 1 and 2. Similarly to period 0, the firm recognizes that by producing in period 1 it remains in business and benefits benefits from period 2 profits, given by $p_H Y$ net of the minimum expected labor costs, $\min(\min(w_{F,O}, E(\omega_O)), \min(w_{F,R}, E(\omega_R)))$. Notice that condition (24) contemplates the case in which, $C_R + \min\left(w_{F,R}; E(\omega_R)\right) > p_H Y$, so that the firm incurs losses in period 1 and still decides to produce, precisely because of the profits it could earn in period 2.

Figure (4) illustrates the optimal strategy of the firm during the pandemic as a function of the worker's skills, s. Note that the optimal strategy of the firm does not involve choosing between business models, as under the pandemic, R is the only feasible business model, as already discussed. The firm's only choice is which incentive scheme to adopt.

Proposition 4 has an immediate corollary

Corollary 2. *In period* 1*, as a consequence of adopting the R model, the firm switches from fixed pay, F, to performance pay, P, if the worker's skills, s, satisfy, $s \in [\widehat{s}_R, \widehat{s}_O)$. Otherwise, the firm either sticks to the incentive scheme F, if $s < \widehat{s}_R$, or to the incentive scheme P, if $s \geq \widehat{s}_O$.*

Proof. See appendix.

The above result states that, during the pandemic, performance pay applies to a wider range of worker's skills, which rationalizes the evidence provided by figure 1 that performance pay has become more popular with the pandemic. Specifically, the widespread adoption of the R model due to the pandemic strengthens the case for performance pay since, under that business model, the monitoring of workers' effort associated with the fixed pay scheme is less effective. That is, the

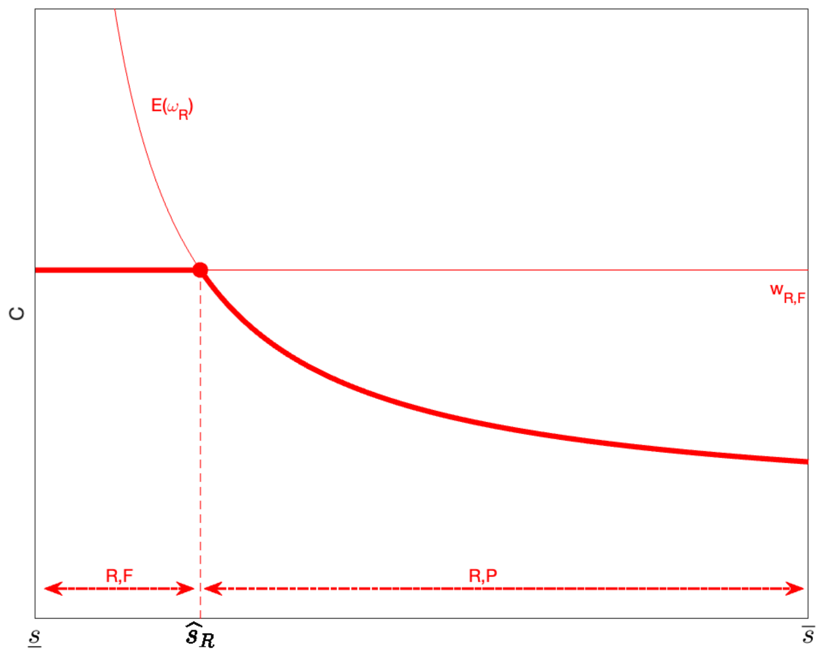


Figure 4: The thick line represents the labor cost associated with the firm's optimal strategy in period 1. The fixed implementation cost is not included as it cancels out since the business model R is the same across incentives schemes.

increased popularity of performance pay stems from the fact that, under the R model, the firm's decision to adopt performance pay is less skill-biased than under the O model.

5.2.3 Period 2: Post-pandemic

In period 2, after the pandemic, the firm has already adopted both business models, making the related fixed implementation costs sunk. Accordingly, the firm's optimal choice, $\{i, j\} \in [\{O, R\} \times \{F, P\}]$, of which business model, $i = O, R$, and incentive scheme, $j = F, P$, to adopt is the one that minimizes the expected labor cost. The following proposition holds

Proposition 5. *In period* 2*, post-pandemic,*

a. If the effectiveness of remote monitoring relative to office monitoring is sufficiently high

$$\frac{\theta_O}{\theta_R} < \alpha_R, \tag{25}$$

the firm adopts $\{R, F\}$ *if* $s \in [\underline{s}, \widehat{s}_R)$, *and* $\{R, P\}$ *if* $s \in [\widehat{s}_R, \overline{s})$;

b. *By contrast, if*

$$\frac{\theta_O}{\theta_R} > \alpha_R, \tag{26}$$

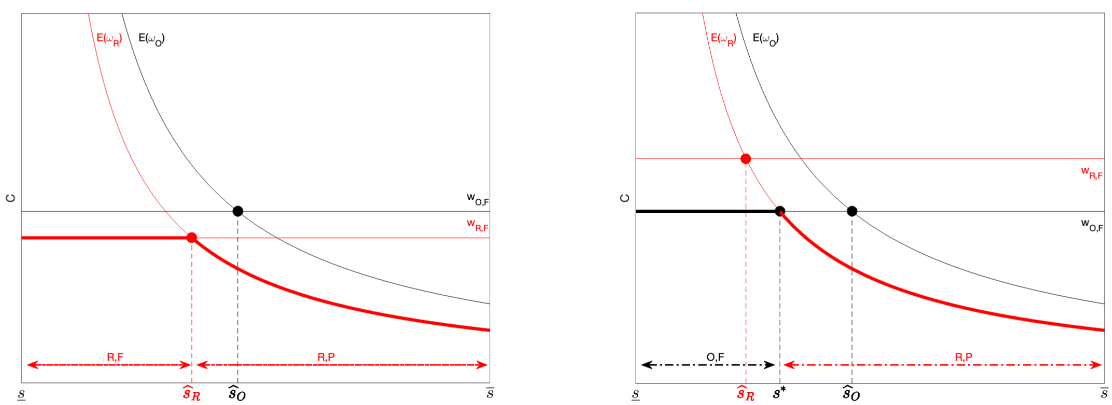
there exist an intermediate level of skills, $s^* \in (\widehat{s}_R, \widehat{s}_O)$, *such that the firm adopts* $\{R, P\}$ *if* $s \in [s^*, \overline{s})$, *and* $\{O, F\}$ *if* $s \in (\underline{s}, s^*)$;

c. *Finally, if*

$$\frac{\theta_O}{\theta_R} = \alpha_R, \tag{27}$$

the firm adopts $\{R, P\}$ *if* $s \in [s^*, \overline{s})$, *and is indifferent between* $\{O, F\}$ *and* $\{R, F\}$ *if* $s \in (\underline{s}, s^*)$, *where* $s^* = \widehat{s}_R = \widehat{s}_O$.

Proof. See appendix.



(a) (b)

Figure 5: The red and black lines represent the labor costs in $t = 2$ when the firm operates the remote and the office models, respectively. The thick line represents the firm's optimal strategy in period 2, when $\alpha_R > \frac{\theta_O}{\theta_R}$ in panel (a), and when $\alpha_R < \frac{\theta_O}{\theta_R}$ in panel (b).

Proposition 5, as illustrated in figure 5, states the main results regarding the structural effects induced by the pandemic that persist afterward, when the O model becomes a viable option again. The first result is the persistence of remote work. Before the pandemic, the firm never adopts the remote model due to its excessive implementation cost. By forcing its adoption, the unforeseen pandemic shock puts the firm in the condition to freely stick to the remote model after the pandemic. Therefore, after the pandemic, the decision to use the remote or the office model no longer depends on implementation costs, which contributes to its persistence. The remote business model surely persists if the worker's skills are high enough that the firm adopts the incentive scheme based on performance pay. Otherwise, the degree of persistence of remote work depends on the efficacy of remote monitoring relative to office monitoring. In the panel (a), of figure 5, condition (25) applies so that the relative efficacy of remote monitoring is high enough that the remote business model dominates the office one irrespective of the incentive scheme adopted by the firm. Differently, in panel (b), the relative efficacy of remote monitoring is so low that if the worker's skill, s are low enough, i.e. $s < s^*$, where $s^* \in (\widehat{s}_R, \widehat{s}_O)$, the firm adopts the incentive scheme based on fixed pay and reverts to the office business model.

The second result is the wider adoption of performance pay after the pandemic, which follows since the adoption of the remote model makes the incentive scheme based on performance more powerful, reducing the expected wage cost faced by the firm as workers prefer to work from home. The result hinges on two drivers. First, for any given level of skills, $\{R, P\}$ dominates $\{O, P\}$ so that when a worker is skilled enough that performance pay is the optimal scheme under the O business model, performance pay under the R model is preferable. Second, the minimum level of skills for the performance pay scheme to be preferable under the O model is higher than the corresponding value under the R model, so that for workers with an intermediate level of skills, $s \in [\widehat{s}_R, \widehat{s}_O)$ such that fixed pay would be preferable under the O model, performance pay under the R model is the optimal choice.[21]

The third result is that remote work is skill-biased. When performance pay is the preferable incentive scheme, R is the optimal business model. Then, since performance pay is preferable if the workers' skills are sufficiently high, see proposition 2, remote work is skill-biased. Finally, this leads to the conclusion that remote work and performance pay are complements, consistent with the evidence of figure 2.

[21]The evidence based on figure 2 suggests that, after the pandemic, firms use performance pay under both business models. However, performance pay is more frequently observed under the R model, consistent with the dominance of $\{R, P\}$ vs. $\{O, P\}$. Of course, other forces justify the use of performance pay under the O model beyond those considered in our setup, which implies that such a dominant result should not be interpreted literally.

5.3 Empirical implications

The model rationalizes the descriptive evidence presented in Section 2 regarding:

i. the surge in remote work and performance-pay jobs observed during the pandemic and their persistence afterward (see Figure 1);

ii. the complementarity between remote work and performance pay (see Figure 2, and Table 1);

iii. the skill bias in remote work and performance pay (see Table 2).

Last but not least, Proposition 5 delivers a testable prediction that is specifically tied to a key mechanism underlying the model. This proposition states that, post-pandemic, the firm sticks to the remote model regardless of the worker's skills if the relative efficacy of office monitoring is sufficiently high. In contrast, if the relative efficacy of remote monitoring is sufficiently low (case b), the firm sticks to the remote model only if the worker is skilled enough to be effectively incentivized with performance pay. Otherwise, if the worker is too unskilled, making fixed pay with monitoring the preferable incentive scheme, the firm reverts to the office model as remote monitoring is ineffective. These two cases can be interpreted as the initial and final stages of the structural transition triggered by the introduction of more restrictive legislation that significantly reduces the efficacy of remote monitoring. Accordingly, the model predicts that an exogenous decline in the relative efficacy of remote monitoring, driven by stricter regulations, should lead to a reduction in remote work among less-skilled workers, if any, while having no significant impact on more-skilled ones. The next section develops an empirical strategy based on this intuition to test the empirical relevance of the theoretical mechanism underlying the model.

6 Efficacy of remote monitoring and remote work

In this section, we present the empirical analysis aimed to test above mentioned prediction. To this aim, we use the Survey of Working Arrangements and Attitudes dataset by (Barrero et al., 2021), henceforth SWAA, which 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.[22] The SWAA dataset provides

[22]The dataset is currently updated monthly (see: https://wfhresearch.com/data/). The results reported in this version of the paper are based on a release of the dataset that includes information from May 2020 to February 2024.

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.

In the United States, electronic monitoring is a common practice and employers have considerable rights to monitor their employees' activities.[23] Employers use various methods to monitor their workers. Among those, the most relevant to our analysis is the use of monitoring software applied to companies' and personal electronic devices. Employers use such monitoring software to track employee activities, including computer and internet usage, email content, and keystrokes. The software solutions addressing such needs are standardized and provided by third parties, which ensures adherence to legal requirements and company policies.

At the federal level, laws provide the main principles regulating this widespread practice without setting specific rules.[24] Therefore, states can implement their own rules, potentially creating variations in the regulations of remote monitoring across the US and over time. We exploit the over time variation within the state of New York to estimate a DiD model for the effect of such a law on remote work. In particular, we evaluate the effect on the workers' share of remote work days over total working days. First, we estimate the DiD on the sub-sample of low-skill workers and find a negative and significant effect. Second, we evaluate the same specification on the sample of high-skill workers, finding no effect. These results, which support the model's predictions, hold through when we estimate a triple DiD, as reported in Appendix B.1.

6.1 The case of New York state

The state of New York regulated electronic monitoring only after 2020, following the surge of remote work due to the pandemic. Specifically, with the bill S2628 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.[25]

[23]Despite the lack of direct evidence on this aspect, the rich supply of monitoring software solutions from US-based companies corroborates such a statement, together with anecdotal evidence provided by discussion forums on the matter.

[24]The main laws regulating the phenomenon at the federal level are the Electronic Communications Privacy Act (ECPA), Computer Fraud and Abuse Act (CFAA), and Stored Communications Act (SCA).

[25]The law states the following: "Employers engaged in electronic monitoring; prior notice required. For purposes of this section, 'employer' means any individual, corporation, partnership, firm, or association with a place of business in

Clearly, the purpose of the law is to protect employee privacy and ensure transparency in monitoring practices. By notifying employees of electronic monitoring, employers make the former aware of the consequences of inappropriate activities. Additionally, informing them of surveillance practices enables employees to make informed decisions about their activities during working hours. Based on the bill's provisions, the law came into effect on the one-hundred-eightieth day after its enactment. Accordingly, after the signing of the bill in November 2021, the law came into effect in May 2022. Such a provision allows employers a reasonable transition period to adjust their practices and adhere to the new requirements outlined in the legislation.

We interpret the requirement for notice as a restrictive regulation that reduces the efficacy of employers' remote monitoring of employees. First, the worker, aware of the monitoring activities implemented by the employer, can take countermeasures and find ways to evade the remote monitoring system. Second, if the employer is forced to inform workers about the monitoring, it might decide to avoid the most invasive (thereby more effective) practices to preserve workers' loyalty. In all instances, the result is a potentially significant reduction of the employer's set of remote monitoring possibilities.[26]

The implementation of such a law creates a discontinuity in the legislative framework within the time frame in which we have information about remote work in our sample.[27] The discontinuity offers an appealing empirical setting to identify the mechanism formalized in proposition 5. Therefore, we exploit this variation to evaluate the effect of a reduction in the monitoring effectiveness on the share of remote work days over total working days, through a DiD analysis. Based on the

the state. It does not include the state or any political subdivision of the state. Any employer who monitors or otherwise intercepts telephone conversations or transmissions, electronic mail or transmissions, or internet access or usage of or by an employee by any electronic device or system, including but not limited to the use of a computer, telephone, wire, radio, or electromagnetic, photoelectronic, or photo-optical systems, must give prior written notice upon hiring to all employees who are subject to electronic monitoring. The notice must be provided in writing, in an electronic record, or in another electronic form, and acknowledged by the employee either in writing or electronically. The employer must also post the notice of electronic monitoring in a conspicuous place that is easily accessible for viewing by employees subject to electronic monitoring. Employees must be informed that any and all telephone conversations or transmissions, electronic mail or transmissions, or internet access or usage by an employee by any electronic device or system, including but not limited to the use of a computer, telephone, wire, radio, or electromagnetic, photoelectronic, or photo-optical systems, may be monitored or intercepted. This format maintains the content without numbered sections or letters."

[26] Alternatively, one might think that, by making employees aware of remote monitoring, would lead them to exert effort and reinforce the mitigation of moral hazard. If this is the case, we should expect an increase in remote work after the law is implemented, as the effectiveness of remote monitoring would improve.

[27] Differently, in Delaware and Connecticut, the more restrictive laws were introduced before 2020.

prediction of the model, the effect of the law in New York should affect only less skilled workers.

On average, workers in New York go little to the office, as illustrated in Figure B.2. This observation motivates us to select the control group for the DiD by including states which exhibit a sufficiently high average share of remote work.[28] The selection of states falling into the control group allows us to obtain more accurate estimates, since we want to compare New York with states that behave similarly in terms of working arrangements. Table 7 presents the summary statistics about the state of New York and the control group for the period employed in the DiD estimation, specifically from November 2021 to November 2022. Not only do New York workers go to the office less frequently, but they are also, on average, more educated, younger, and with a higher income.

A visual inspection of figure 6 shows the drop in the share of remote work for low-skilled workers in New York after the introduction of the regulation. Despite the peak at the treatment date, corresponding to the vertical dashed line, remote work decreases rapidly for low-skilled workers in New York while low-skilled in other states do not exhibit any significant change. In general, excluding low-skilled that are treated, the other workers do not experience any significant change in their share of remote work days.

To evaluate the effect of a more restrictive regulation on workers' share of remote work paid days, we estimate the same specification on two different sub-samples: low-skilled and high-skilled workers. By restricting the sample to low-skilled workers, we estimate the average treatment effect by taking the relative differences between treated (low-skilled New Yorkers) and control (low-skilled in other states) with respect to the share of remote work post- and pre-treatment. Accordingly, the same applies to the sub-sample of high-skilled workers. 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 workers' remote work days over total working days. This estimation fails to account for persistent economic disparities among states, which can be mitigated by including time and state fixed effects. An alternative approach would be to estimate the DiD by restricting the sample to New Yorkers, and take the relative differences between high-skill and low-skill workers. However,

[28] Specifically, the baseline estimation includes states with an average share of remote work above the median of the distribution of remote work across states. Results hold also by including all states in the estimation, see appendix B.2.

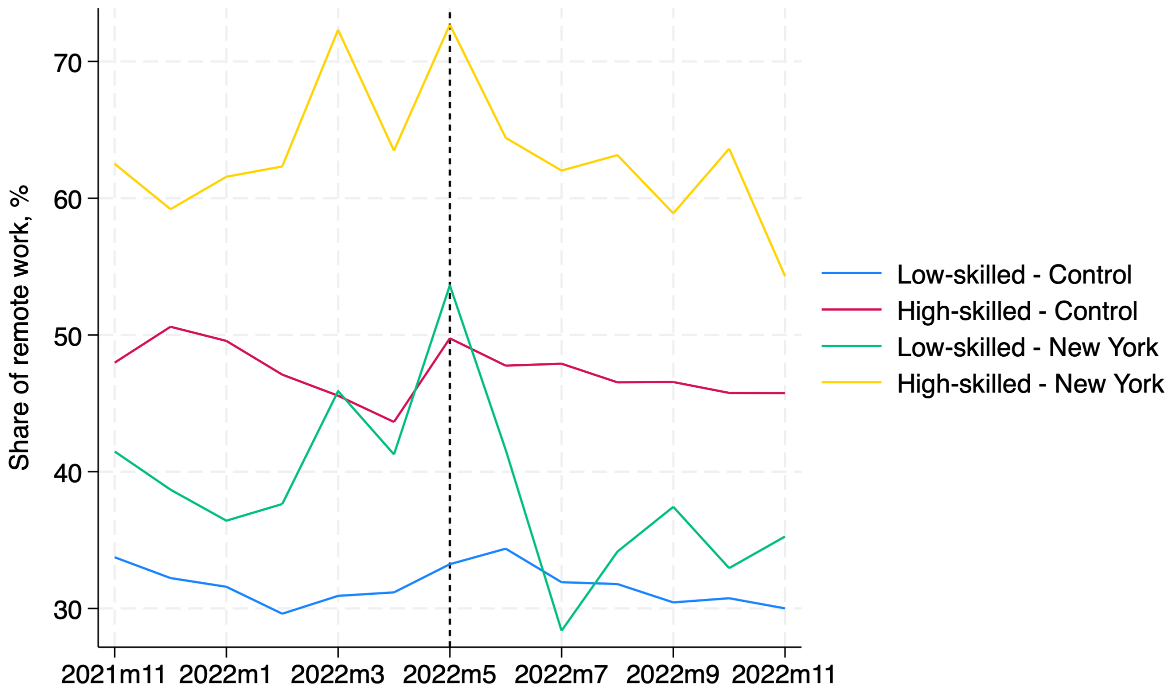


Figure 6: Unconditional average of the share of remote work over total working days for workers in New York and control states, by skill. The vertical dashed line identifies the treatment date, i.e. May 2022.

this would not yield robust estimates as long as the legislation has within-state spillover, which we believe is the case. By within-state spillovers we mean that, upon the reduction of monitoring effectiveness for low-skilled workers, the employer likely mandates a generalized return to the office, with high-skilled workers called back to the business premises together with low-skill for better workflow coordination. Finally, an additional avenue is to estimate a triple DiD by taking the relative differences between both states' and skills' groups. The triple interaction allows us to account for persistent economic differences across states and within-state spillovers. However, it is not able to account for trending differences across skill groups which may affect the results. In the appendix, we perform all the outlined alternatives. Despite differences in terms of magnitude, all results point in the same direction: the regulation had a negative impact on the share of remote work for low-skilled workers in New York.

To establish the counterfactuals, we estimate the following specification

$$Y_{i,t} = \alpha + \beta_1 \text{Post}_t + \beta_2 \text{Treat}_i + \beta_3 \text{Post}_t \times \text{Treat}_i + X'_{i,t}\delta + A'_{i,t}\gamma + \epsilon_{i,t}, \tag{28}$$

where $Y_{i,t}$ represents the share of remote work paid days over total working 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 resides 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. As anticipated, we estimate equation (28) on the sample of low-skill and high-skill workers once a time. We use education as a proxy for skills. Therefore, the sub-sample of low-skilled workers is composed of those who do not have a college degree. Conversely, the sub-sample of high-skill workers is composed of those having at least a college degree. Since education is an imperfect proxy for skills, we control for the (log of) income, other than the gender.[29] 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-month window, 6 months before and 6 after the treatment date. Hence, the sample goes from November 2021 to November 2022.

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 workers post- and pre-treatment in New York, and (ii) the change in the share of remote work days of workers post- and pre-treatment in states belonging to the control group. A negative coefficient would indicate that, after the introduction of the legislation, workers in New York saw a decrease in 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 workers in the treated state. Results reported in columns (1) and (2) of Table 3 show that the effect is significant and negative for low-skilled workers. The negative effect for low-skilled holds after controlling for observables

[29] As pointed out in Olden and Møen (2022), the inclusion of control variables with substantial explanatory power increases the accuracy of the estimate and reduces the residual variance not explained by the econometric model. Furthermore, it does account for compositional differences that may be present across states, which is the case in our setting (see figure B.2).

% Remote Work	Low-skilled (1)	(2)	High-skilled (3)	(4)
Treat	4.874***		12.27***	
	(1.293)		(1.004)	
Post	-0.136		-1.354	
	(1.014)		(1.035)	
Treat × Post	**-2.674****	**-2.623****	**0.544**	**1.545**
	(1.014)	(1.000)	(1.035)	(1.051)
Constant	34.81***	42.43***	50.84***	51.68***
	(1.293)	(1.064)	(1.004)	(0.504)
Observations	14,107	14,107	21,331	21,331
R-squared	0.000	0.120	0.013	0.100
Controls	✗	✓	✗	✓
Fixed effects	✗	✓	✗	✓
Clust. errors	State-level	State-level	State-level	State-level

Table 3: DiD on sub-samples: low-skilled and high-skilled workers, NY vs the control group. Columns (1) and (2) report the results for the estimation on the sub-sample of low-skilled workers, while (3) and (4) on the subsample of high-skilled workers. The estimation is performed in a 12-month 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 parenthesis (*** p<0.01, ** p<0.05, * p<0.1).

and beyond time, age, industry and state fixed effects, as shown in column (2), and establishes at around a negative 2.6%. While columns (3) and (4) show there is no effect for high-skilled workers. The results produced by the estimation of the DiD provide robust evidence supporting the empirical prediction of the model as of proposition 5.

Figure B.1 reports the event study that shows the changes in the outcome variable for low-skilled workers, i.e., the β_3 for the estimate performed on the sub-sample of low-skill, around the treatment date. Despite some fluctuations during the pre-treatment period, post-treatment the effect is consistently negative after July 2022. The effect estimated with the DiD also supports the mechanism outlined in proposition 5.

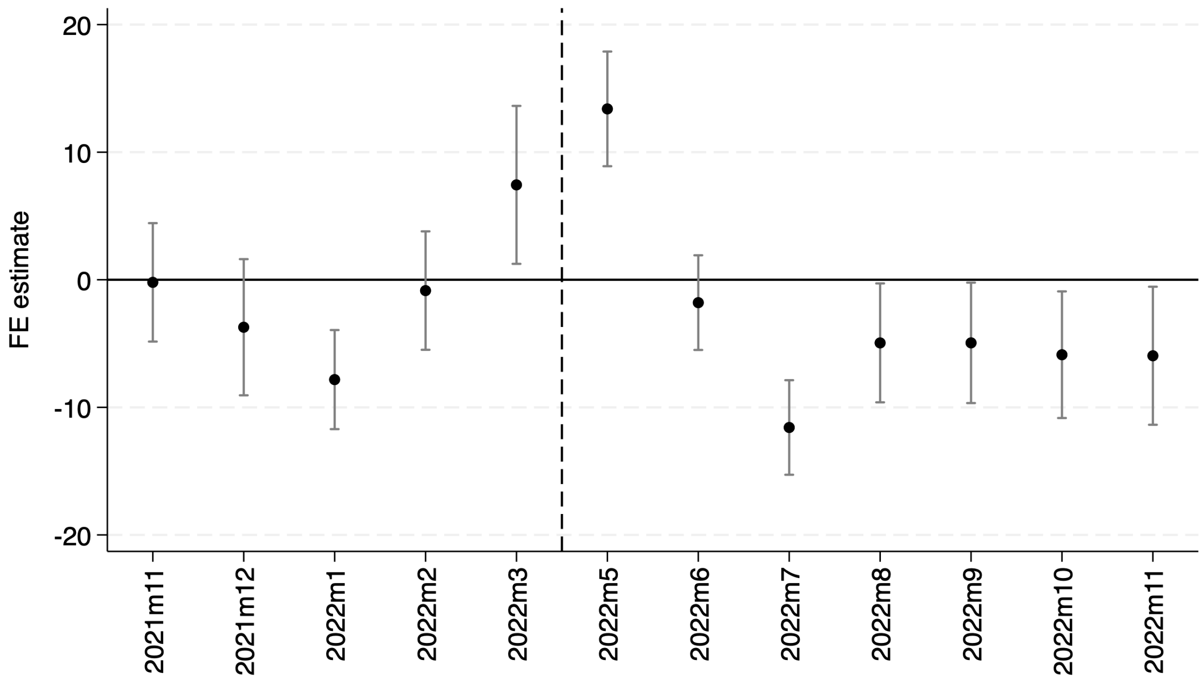


Figure 7: Event-study for low-skilled workers for the 12-month window estimation. Estimates are with respect to the month preceding the treatment date, i.e. April 2022, which is omitted in the graph.

7 Conclusion

We document novel facts about working arrangements since the pandemic: the increased popularity of performance pay concurrent to the rise in remote work, a robust complementarity between the two and their skill-biased nature. We present a parsimonious model that explains such evidence. A crucial prediction of the model is that an decline in the effectiveness of remote monitoring of workers' effort should lead to a reduction of remote work only among low-skill workers, if any. Our empirical findings strongly support this prediction and, combined with the motivating descriptive evidence we provide, further validate the model's underlying mechanism. The simplicity of the theoretical framework we develop opens the way for further extensions in various directions, including firm entry, wage determination in labor markets populated by many workers and firms, and the role of worker and firm heterogeneity in shaping skill-biased technological progress. Our analysis suggests that pandemic policies and regulations may have had a lasting structural impact on the diffusion of remote work and performance pay. Finally, given the documented impact of remote work and performance pay on workers' health in the literature, our findings have non-trivial implications for work-life balance, employee stress, and job satisfaction.

References

Aksoy, C. G., Barrero, J. M., Bloom, N., Davis, S. J., Dolls, M., and Zarate, P. (2022). Working from home around the world. Technical report, National Bureau of Economic Research.

Aksoy, C. G., Barrero, J. M., Bloom, N., Davis, S. J., Dolls, M., and Zarate, P. (2023). Time savings when working from home. In *AEA Papers and Proceedings*, volume 113, pages 597–603. American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203.

Autor, D. H. and Dorn, D. (2013). The growth of low-skill service jobs and the polarization of the us labor market. *American Economic Review*, 103(5):1553–1597.

Bandiera, O., Guiso, L., Prat, A., and Sadun, R. (2015). Matching firms, managers, and incentives. *Journal of Labor Economics*, 33(3):623–681.

Barrero, J. M., Bloom, N., and Davis, S. J. (2021). Why working from home will stick. Technical report, National Bureau of Economic Research.

Barrero, J. M., Bloom, N., and Davis, S. J. (2023). The evolution of work from home. *Journal of Economic Perspectives*, 37(4):23–49.

Bick, A., Blandin, A., and Mertens, K. (2023). Work from home before and after the covid-19 outbreak. *American Economic Journal: Macroeconomics*, 15(4):1–39.

Cerina, F., Dienesch, E., Moro, A., and Rendall, M. (2023). Spatial polarisation. *The Economic Journal*, 133(649):30–69.

Chetty, R. (2006). A new method of estimating risk aversion. *American Economic Review*, 96(5):1821–1834.

Cohen, A. and Einav, L. (2007). Estimating risk preferences from deductible choice. *American Economic Review*, 97(3):745–788.

Cullen, Z. B., Pakzad-Hurson, B., and Perez-Truglia, R. (2025). Home sweet home: How much do employees value remote work? Technical report, National Bureau of Economic Research.

Dingel, J. I. and Neiman, B. (2020). How many jobs can be done at home? *Journal of Public Economics*, 189:104235.

Eriksson, T. and Villeval, M. C. (2008). Performance-pay, sorting and social motivation. *Journal of Economic Behavior & Organization*, 68(2):412–421.

Ewing, B. T. (1996). Wages and performance-based pay: Evidence from the nlsy. *Economics Letters*, 51(2):241–246.

Hansen, S., Lambert, P. J., Bloom, N., Davis, S. J., Sadun, R., and Taska, B. (2023). Remote work across jobs, companies, and space. Technical report, National Bureau of Economic Research.

Hsu, D. H. and Tambe, P. B. (2025). Remote work and job applicant diversity: Evidence from technology startups. *Management Science*, 71(1):595–614.

Ko, Y. K. and Baek, I. G. (2024). The effect of computer monitoring on employees' productivity in telecommuting arrangements. *Management Science*, 71(1):103–122.

Lamorgese, A., Patnaik, M., Linarello, A., and Schivardi, F. (2024). Management practices and resilience to shocks: Evidence from covid-19. *Management Science*.

Lazear, E. P. (1986). Salaries and piece rates. *The Journal of Business*, 59(3):405–431.

Lazear, E. P. (2000). Performance pay and productivity. *American Economic Review*, 90(5):1346–1361.

Lazear, E. P. (2018). Compensation and incentives in the workplace. *Journal of Economic Perspectives*, 32(3):195–214.

Maestas, N., Mullen, K. J., Powell, D., Von Wachter, T., and Wenger, J. B. (2023). The value of working conditions in the united states and implications for the structure of wages. *American Economic Review*, 113(7):2007–2047.

Mas, A. and Pallais, A. (2017). Valuing alternative work arrangements. *American Economic Review*, 107(12):3722–3759.

Olden, A. and Møen, J. (2022). The triple difference estimator. *The Econometrics Journal*, 25(3):531–553.

Pei, Z., Pischke, J.-S., and Schwandt, H. (2019). Poorly measured confounders are more useful on the left than on the right. *Journal of Business & Economic Statistics*, 37(2):205–216.

Zarate, P., Dolls, M., Davis, S. J., Bloom, N., Barrero, J. M., and Aksoy, C. G. (2024). Why does working from home vary across countries and people? Technical report, National Bureau of Economic Research.

Appendix

A Analytical Proofs

A.1 Proof of proposition 1

The derivative of $E(\omega_i)$ with respect to s is

$$\frac{\partial E(\omega_i)}{\partial s} = \left(w_{H,i} - w_{L,i} + \sigma_{H,H} \frac{\partial w_{H,i}}{\partial \sigma_{H,H}} \right) \frac{d\sigma_{H,H}}{ds} \tag{A.1}$$

where $w_{L,i}$, $w_{H,i}$ and $E(\omega_i)$ are given respectively by (18), (19) and (20). Applying the theorem of the inverse function,

$$\frac{\partial w_{H,i}}{\partial \sigma_{H,H}} = -\frac{1}{f'(w_{H,i})} \frac{g(e_H) - g(e_L)}{\alpha_i (1-\beta) (\sigma_{H,H})^2} \tag{A.2}$$

so that

$$\frac{\partial E(\omega_i)}{\partial s} = \left(w_{H,i} - w_{L,i} - \frac{1}{f'(w_H)} \frac{g(e_H) - g(e_L)}{\alpha_i (1-\beta) \sigma_{H,H}} \right) \frac{d\sigma_{H,H}}{ds} \tag{A.3}$$

which, using (16), can be rewritten as

$$\frac{\partial E(\omega_i)}{\partial s} = \left(w_{H,i} - w_{L,i} - \frac{f(w_H) - f(w_{L,i})}{f'(w_{H,i})} \right) \frac{d\sigma_{H,H}}{ds} \tag{A.4}$$

To study the sign of this derivative we can focus only on the term inside brackets since, by assumption 1, $\frac{d\sigma_{H,H}}{ds} > 0$. Recall that a worker is risk-averse if $f(\cdot)$ is strictly concave, risk-lover if $f(\cdot)$ is strictly convex and risk-neutral if $f(\cdot)$ is linear. Accordingly, assume $f(\cdot)$ is strictly concave (strictly convex). Then

$$w_{H,i} - w_{L,i} < (>) \frac{f(w_{H,i}) - f(w_{L,i})}{f'(w_{L,i})} \tag{A.5}$$

and

$$f'(w_{H,i}) < (>) f'(w_{L,i}) \tag{A.6}$$

which jointly imply

$$w_{H,i} - w_{L,i} < (>) \frac{f\left(w_{H,i}\right) - f\left(w_{L,i}\right)}{f'\left(w_{H,i}\right)} \tag{A.7}$$

Then, given (A.4), $\frac{\partial E(\omega_i)}{\partial s} < (>) 0$ follows, so that we conclude that $E(\omega_i)$ is strictly decreasing (increasing) in s, if and only if the worker is risk-averse (-lover).

Finally, in the special case of the linearity of $f(\cdot)$, the following expressions hold

$$w_{H,i} - w_{L,i} = \frac{f\left(w_{H,i}\right) - f\left(w_{L,i}\right)}{f'\left(w_{L,i}\right)} \tag{A.8}$$

and

$$f'\left(w_{H,i}\right) = f'\left(w_{L,i}\right) \tag{A.9}$$

which jointly imply

$$w_{H,i} - w_{L,i} = \frac{f\left(w_{H,i}\right) - f\left(w_{L,i}\right)}{f'\left(w_{H,i}\right)} \tag{A.10}$$

Then, given (A.4), $\frac{\partial E(\omega_i)}{\partial s} = 0$ follows, so that we conclude that $E(\omega_i)$ is unaffected by s, if and only if the worker is risk-neutral.

A.2 Proof of proposition 2

In any period and for a given business model $i = O, R$, the firm chooses P over F if $E(\omega_i) \leq w_{F,i}$, where, given (12), (18), (19), and (20) and assumption 3,

$$w_{F,i} = \left(\frac{g(e_H) - g(e_L)}{\alpha_i \theta_i}\right)^{\frac{1}{\gamma}} \tag{A.11}$$

$$\begin{aligned} E(\omega_i(s)) &= \left(\frac{g(e_L) - \beta g(e_H)}{\alpha_i(1-\beta)}\right)^{\frac{1}{\gamma}} \\ &+ \sigma_{H,H}(s) \left(\frac{(1 - \beta\sigma_{H,H}(s))g(e_H) - (1 - \sigma_{H,H}(s)g(e_L)}{\alpha_i(1-\beta)\sigma_{H,H}(s)}\right)^{\frac{1}{\gamma}} \end{aligned} \tag{A.12}$$

We note that, while $w_{F,i}$ does not depend on skills, s, $E(\omega_i)$ is strictly decreasing in s so long as the worker is risk-averse ($\gamma < 1$) as stated by proposition 1. Therefore, under worker's risk-aversion, if any, there is at most one threshold value of s,

$$\widehat{s}_i : E(\omega_i(s)) \equiv w_{F,i}, \tag{A.13}$$

with $E(\omega_i) > (\leq) w_{F,i}$ for $s < (\geq) \widehat{s}_i$. Then, recalling that by assumption 1 $\sigma_{H,H}$ is an increasing function of s, we have

$$\lim_{s \to \underline{s}} E(\omega_i(s)) = \left(\frac{g(e_L) - \beta g(e_H)}{\alpha_i(1-\beta)}\right)^{\frac{1}{\gamma}} + \left(\frac{g(e_H) - g(e_L)}{\alpha_i\,(1-\beta)}\right)^{1/\gamma} \lim_{s \to \underline{s}} \sigma_{H,H}^{-\frac{1-\gamma}{\gamma}}(s) = \infty \tag{A.14}$$

since $\gamma < 1$. Furthermore,

$$\lim_{s \to \overline{s}} E(\omega_i(s)) = \left(\frac{g(e_H)}{\alpha_i}\right)^{\frac{1}{\gamma}} \tag{A.15}$$

Therefore, by comparing the above expression with equation (A.11) it follows that a unique threshold value $\widehat{s}_i$ exists if and only if

$$\frac{g(e_H)}{\alpha_i} < \frac{g(e_H) - g(e_L)}{\alpha_i \theta_i} \tag{A.16}$$

which is always true under assumption 2.$\square$

A.3 Proof of Corollary 1

Based on proposition 2, the threshold value of the worker's skills, $\widehat{s}_i$, associated with the firm's decision on how to incentivize the worker, depending on the adopted business model, $i = O, R$, recalling that $\alpha_R > \alpha_O \equiv 1$, is:

$$\widehat{s}_R \quad : \quad \sigma_{H,H}(\widehat{s}_R)\alpha_R^{-\frac{1}{\gamma}} a_H + \left[1 - \sigma_{H,H}(\widehat{s}_R)\right] \alpha_R^{-\frac{1}{\gamma}} a_L = (\alpha_R \theta_R)^{-\frac{1}{\gamma}} a_F \tag{A.17}$$

$$\widehat{s}_O \quad : \quad \sigma_{H,H}(\widehat{s}_O) a_H + \left[1 - \sigma_{H,H}(\widehat{s}_O)\right] a_L = \theta_O^{-\frac{1}{\gamma}} a_F, \tag{A.18}$$

where, using assumption 3, we rewrite salaries, originally defined by equations (18) and (19), as

$$w_{H,i} = \alpha_i^{-\frac{1}{\gamma}} a_H \tag{A.19}$$

$$w_{L,i} = \alpha_i^{-\frac{1}{\gamma}} a_L \tag{A.20}$$

$$w_{F,i} = (\alpha_i \theta_i)^{-\frac{1}{\gamma}} a_F, \tag{A.21}$$

with,

$$a_H \equiv \left(\frac{(1-\sigma_{H,H}\beta)\, g(e_H) - (1-\sigma_{H,H})\, g(e_L)}{\sigma_{H,H}\,(1-\beta)}\right)^{\frac{1}{\gamma}} \tag{A.22}$$

$$a_L \equiv \left(\frac{g(e_L) - \beta g(e_H)}{(1-\beta)}\right)^{\frac{1}{\gamma}} \tag{A.23}$$

$$a_F \equiv (g(e_H) - g(e_L))^{\frac{1}{\gamma}} \tag{A.24}$$

It is immediate to verify that (A.17) and (A.18) reduce to

$$\widehat{s}_R \ : \ \sigma_{H,H}(\widehat{s}_R)a_H + (1-\sigma_{H,H}(\widehat{s}_R))a_L = \theta_R^{-\frac{1}{\gamma}} a_F \tag{A.25}$$

$$\widehat{s}_O \ : \ \sigma_{H,H}(\widehat{s}_O)a_H + (1-\sigma_{H,H}(\widehat{s}_O))a_L = \theta_O^{-\frac{1}{\gamma}} a_F \tag{A.26}$$

Finally, since the values of the LHS of the two equations are evaluations of the same strictly decreasing function at $\widehat{s}_R$ and $\widehat{s}_O$ (see proposition (1)), $\theta_R < \theta_O$ directly implies $\widehat{s}_R < \widehat{s}_O$. $\square$

A.4 Proof of proposition 3

In period 0, the firm finds convenient to produce if the implementation cost of the preferred model is lower than the total expected revenues over the three periods net of the total labor costs, which leads to condition(23). This directly follows from the fact that having chosen a business model in a certain period, the firm has the option of sticking to it in the future, which proves the first of the proposition.

As for the second part, the following applies. When assessing the firm's choice of business model in period 0, we should compare the expected costs of choosing that model and sticking to it with the expected costs of choosing that model and switching to other models in future periods. Define $Z(i_0, i_1, i_2)$ the total expected cost - including the one-time implementation cost of the business model and the workers' pay - incurred by the firm when choosing the business model i_0 in 0, i_1 in period 1 and i_2 in period 2. If in periods 1 and 2 the firm sticks to the inherited business model $i = O, R$ chosen in 0, such a cost is

$$Z(i,i,i) = C_i + 3\min(E(\omega_i), w_{F,i}) \tag{A.27}$$

If the firm's choice (i_0, i_1, i_2) is such that $(i_0, i_1, i_2) \in \{(R, R, O), (R, O, R), (O, R, R)\}$, so that the firm adopts the O model only in one period, then

$$Z(R, R, O) = Z(R, O, R) = Z(O, R, R) = C_R + C_O + 2\min(E(\omega_R), w_{F,R}) + \min(E(\omega_O), w_{F,O}) \tag{A.28}$$

Differently, if $(i_0, i_1, i_2) \in \{(R, O, O), (O, R, O), (O, O, R)\}$, so that the firm uses the model R only once,

$$Z(R, O, O) = Z(O, R, O) = Z(O, O, R) = C_R + C_O + 2\min(E(\omega_O), w_{F,O}) + \min(E(\omega_R), w_{F,R}) \tag{A.29}$$

Given (A.27), (A.28) and (A.29), in period 0, the total expected cost of choosing model O, sticking to it in future periods, is lower than that of any other alternative so long as the following conditions hold

$$Z(O, O, O) < Z(R, R, R) \Leftrightarrow C_R > C_O + 3[\min(E(\omega_O), w_{F,O}) - \min(E(\omega_R), w_{F,R})] \tag{A.30}$$

$$Z(O, O, O) < Z(R, R, O) \Leftrightarrow C_R > 2[\min(E(\omega_O), w_{F,O}) - \min(E(\omega_R), w_{F,R})] \tag{A.31}$$

$$Z(O, O, O) < Z(R, O, O) \Leftrightarrow C_R > [\min(E(\omega_O), w_{F,O}) - \min(E(\omega_R), w_{F,R})] \tag{A.32}$$

Inspection reveals that condition (A.30) is more stringent so that if (A.30) holds, (A.31) and (A.32) are always verified. Moreover, since $Z(R, R, O) = Z(O, R, R)$ and $Z(R, O, O) = Z(O, R, O)$ by (A.28) and (A.29), if condition (A.30) holds, (O, O, O) is the optimal strategy. The rest of the proof, regarding the choice of the incentive scheme, follows directly from proposition 2. □

A.5 Proof of proposition 4

The assumption that the firm goes permanently out of business if it stops operating in one period ensures that the condition (24) is necessary and sufficient for the firm to choose to implement the model R. The rest of the proof, regarding the choice of the incentive scheme, follows directly from proposition 2.□

A.6 Proof of Corollary 2

The proof follows directly from corollary 1.□

A.7 Proof of Proposition 5

At time $t = 2$, the firm has adopted both business models. Therefore, it can either operate the "office" model or the "remote" model with no additional implementation cost. Accordingly, the proof follows immediately from comparing the expected wage costs of the incentive schemes available under the two business models.□

B Additional empirical evidence

B.1 Triple DiD

The triple DiD model allows us to consider the difference between New York and the control group as well as the difference between low- and high-skill workers within states, when assessing the effect of the more restrictive law on remote work. The triple interaction lets us avoid biases arising from persistent economic differences across states and within-state spillover. To establish the counterfactual with a triple DiD model, we estimate the following specification

$$\begin{aligned} Y_{i,t} = \; & \alpha + \beta_1 \text{Post}_t + \beta_2 \text{NY}_i + \beta_3 \text{lowskill}_i + \beta_4 \text{Post}_t \times \text{NY}_i + \beta_5 \text{Post}_t \times \text{lowskill}_i \\ & + \beta_6 \text{NY}_i \times \text{lowskill}_i + \beta_7 \text{Post}_t \times \text{lowskill}_i \times \text{NY}_i + X'_{i,t}\delta + A'_{i,t}\gamma + \epsilon_{i,t}, \end{aligned} \tag{B.1}$$

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, the date in which the restrictive law came into effect, $lowskill_i$ is a dummy that equals 1 if the worker is low-skill (where skills ares 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 the error term. As before, we define low-skill workers those who have not a college degree. The vector of controls includes the log of the income and the gender dummy.[30] Errors are clustered at the state level, and the weights

[30] Following Pei et al. (2019), we test that the introduction of such controls is not a poor measure of the potential underlying confounders. To do so, we perform a balancing test that verifies 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

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 6-months window, 6 months before and 6 after the treatment date. Hence, the sample goes from November 2021 to November 2022.

	(1)	(2)
Dep. Var.	% remote work	% remote work
NY	12.27***	
	(1.004)	
Post	-1.354	
	(1.035)	
Low-skill	-16.03***	-8.917***
	(1.443)	(1.693)
NY × Post	0.544	2.666**
	(1.035)	(0.991)
NY × Low-skill	-7.391***	-2.842*
	(1.443)	(1.390)
Post × Low-skill	1.218	2.648
	(1.769)	(1.571)
NY × Post × Low-skill	-3.218*	-5.245***
	(1.769)	(1.564)
Constant	50.84***	50.60***
	(1.004)	(0.414)
Observations	35,438	35,438
R-squared	0.043	0.131
Controls	✗	✓
Fixed effects	✗	✓
Clust. errors	State-level	State-level

Table 4: 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 parenthesis (*** p<0.01, ** p<0.05, * p<0.1).

The coefficient of interest is β_7, which captures the difference between the change in the share of remote work days for low-skill workers compared to high-skill ones in New York, and the change in the share of remote work days for low-skill workers compared to high-skill ones in the control group, following the treatment. A negative coefficient would indicate that after the introduction

F-test reveals that we cannot reject the null hypothesis, according to which the triple interaction coefficient is equal to zero. It confirms that the coefficient of interest is not affected by the inclusion of those regressors and fixed effects in the regression.

of the more restrictive legislation in NY, in that state low-skilled workers decreased their share of remote work days relative to that of high-skilled ones more than in other states. In other words, a negative β_7 indicates a negative impact of the legislation on the share of remote work days for low-skilled workers in the treated state. The results reported in Table 4, column 2, show that the effect is negative and significant. It suggests that, after the implementation of the restrictive legislation in the state of New York, there has been a drop in the share of remote work days relative to total working days for low-skill workers with respect to high-skilled ones. Nonetheless, the coefficient for high-skill workers in New York, i.e. β_4, is positive and significant suggesting that after the law implementation they increased their share of remote work. This can drive mechanically upward the estimate for our coefficient of interest, i.e. β_7. Therefore, the difference between β_4 and β_7 gives us an effect very similar to the estimation obtained with the double DiD on the subsample of low-skilled workers. The estimates provide additional evidence about the empirical prediction of the model, outlined in proposition 5, according to which a sufficient decrease in monitoring effectiveness induces a relative reduction in remote work by low-skill workers.

Figure B.1 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, validates the parallel trends assumption. However, the other post-treatment periods show negative or zero coefficients, suggesting that the implementation of the legislation has a scattered yet consistently negative effect over time. Also the effect estimated with the triple DiD supports the mechanism outlined in proposition 5.

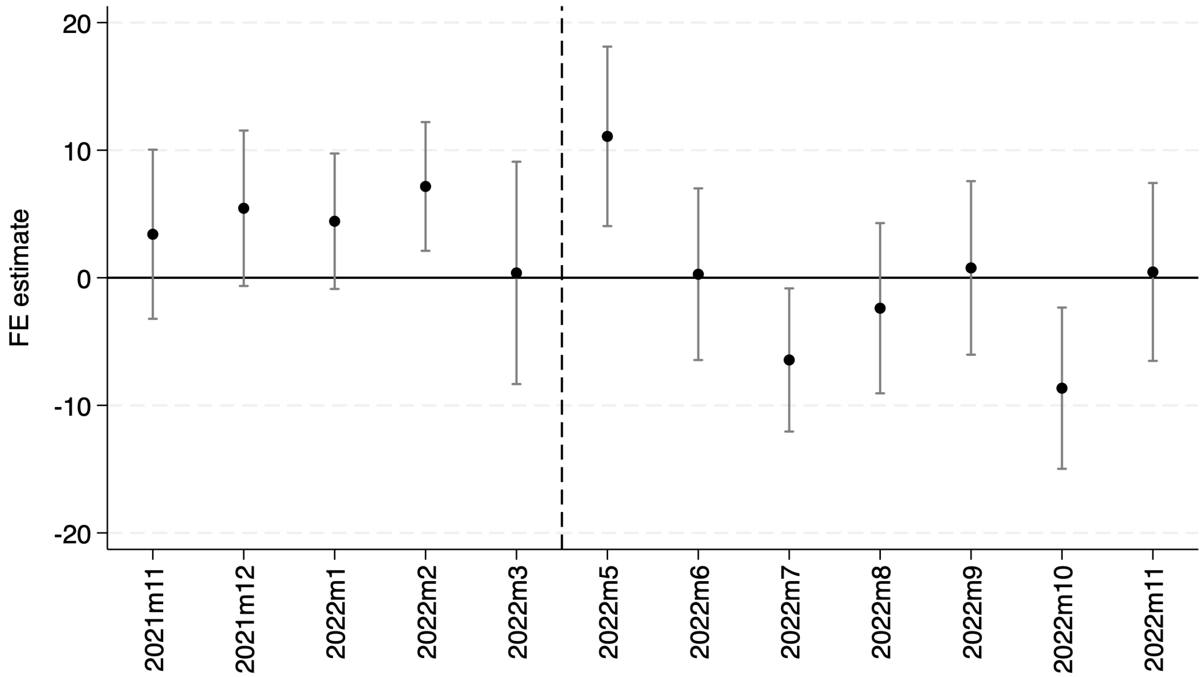


Figure B.1: Event-study for the triple DiD on mandated notice of monitoring in the State of New York. Estimates are with respect to the month preceding the treatment date, i.e. April 2022 which is omitted from the graph.

B.2 Alternative sub-samples

Table 5 report the results of estimating equation 28 while considering different control groups, an alternative dependent variable, and by identifying differently treated workers.

The estimations in columns (1) and (6) include all states, without imposing restrictions on the control group. In contrast, columns (2) and (7) limit the control group to states with a share of low-skill workers below the median. Similarly, columns (3) and (8) modify the control group to include only the 50 most populated CSAs. In columns (4) and (9), the dependent variable is a dummy that takes value 1 if the worker engaged in remote work during the week, and 0 otherwise. The results in columns (5) and (10) are based on identifying treated workers as those residing in New York state while working within the CSA of New York.[31]

[31] The CSA of New York includes regions outside the state of New York that are not subject to the legislation of interest. However, considering moving costs and local labor markets, it is reasonable to assume that individuals residing there are also likely to work within New York state.

	Low-Skill					High-Skill				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Full controls	Skilled states	Top 50 CSAs	Y: dummy	T: CSA	Full controls	Skilled states	Top 50 CSAs	Y: dummy	T: CSA
Treat × Post	-2.896***	-2.364*	-4.248***	-0.983	-6.694***	0.972	1.397	-0.655	-0.241	-0.766
	(0.777)	(1.174)	(1.420)	(1.032)	(1.166)	(0.930)	(1.163)	(1.209)	(1.055)	(1.377)
Constant	38.89***	42.69***	41.40***	39.49***	42.22***	49.70***	52.05***	51.88***	46.94***	52.24***
	(0.854)	(1.057)	(1.091)	(1.144)	(0.872)	(0.477)	(0.564)	(0.612)	(0.609)	(0.745)
Observations	22,742	12,055	11,412	14,107	13,816	26,866	20,219	17,689	21,331	20,577
R-squared	0.112	0.122	0.126	0.101	0.124	0.100	0.103	0.111	0.070	0.106
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Fixed effects	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Clust. errors	State-level	State-level	State-level	State-level	CSA-level	State-level	State-level	State-level	State-level	CSA-level

Table 5: Alternative double DiD. (1) and (6) include all states as controls. In (2) and (7) only states with a share of low-skill workers below the median. (3) and (8) include top 50 CSAs in terms of population. The dependent variable is a dummy for remote work in (4) and (9). (5) and (10) identify treated workers as those residing in the NY state and working within the CSA of NY. 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 and reported in parenthesis (*** p<0.01, ** p<0.05, * p<0.1).

B.3 Summary Statistics

Table 6: Summary Statistics about over the entire sample

	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

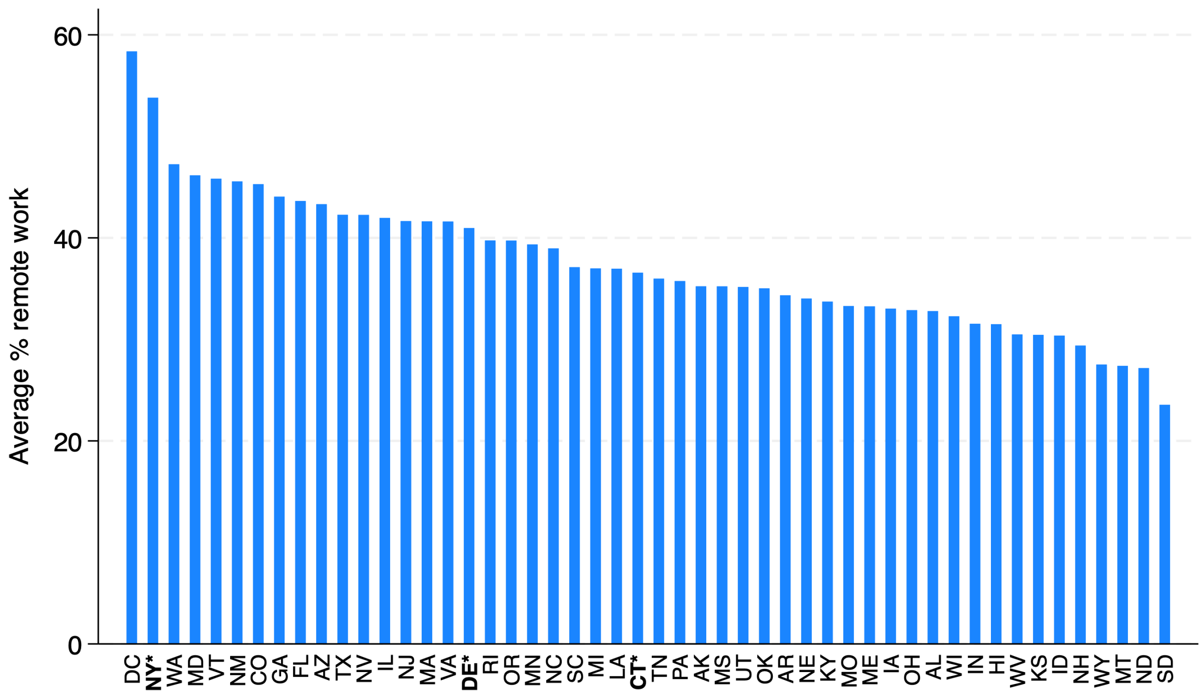


Figure B.2: Weighted average share of remote work days, by state. States highlighted in bold and with the asterisk are the 'treated' states, those with low-effectiveness of monitoring due to legislative restrictions.

Table 7: Summary Statistics sample estimation for the DiD, NY vs control group

	Mean	SD	N
Control group			
Remote work, %	41.34	45.57	27780
Years of Education	14.65	2.32	27780
2019 Earnings, $ Thousand	62.46	82.11	27780
Age	42.31	11.60	27780
New York			
Remote work, %	54.67	44.22	7658
Years of Education	15.79	2.40	7658
2019 Earnings, $ Thousand	94.26	124.60	7658
Age	41.00	10.02	7658
Total			
Remote work, %	43.15	45.62	35438
Years of Education	14.80	2.37	35438
2019 Earnings, $ Thousand	66.77	89.73	35438
Age	42.13	11.40	35438

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