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Remote Work Intensity and Wages: Evidence from a Representative Canadian Labour Force Survey

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Abstract

Flexible work arrangements are increasingly becoming the norm across many countries, particularly in developed nations such as Canada and the United States. Remote work (work-from-home, or WFH, for short) has gained significant popularity in recent years, especially after the outbreak of the COVID-19 pandemic in March 2020. Building on seminal contributions by Bloom et al. (2015) and Davis (2024), we develop a simple theoretical model that captures the trade-off between externalities associated with remote work and those derived from in-office work. The model is based on the premise that both productivity and firm profitability are influenced by the intensity or proportion of remote work arrangements by firms. Ultimately, higher workforce productivity and firm profitability due to remote work translate into higher wages. By considering different collaboration structures among employees, the model demonstrates that while remote work can lead to cost savings and positive externalities, excessive adoption may undermine benefits, increase management complexity, and raise the risk of employee shirking. The central theoretical result is an inverted U-shaped relationship between the extent of remote work and wages. To test this prediction, we use data from the Canadian Labour Force Survey to examine the relationship between industry-level remote work intensity and individual wages. The empirical findings reveal that wages rise with remote work intensity up to a threshold, approximately 52.1–63.9%, beyond which they begin to decline, supporting the model's non-linear prediction.

JEL classification

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Keywords

work from home, remote work, wages, productivity, externality

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1. Introduction

The advancement of information and telecommunication technology (ICT), combined with the rise of web interfaces in the 1990s, made it possible for many people to work from home or, more broadly, to perform jobs remotely, also referred to as teleworking. While only about 6.5% of private-sector employees in the U.S. worked remotely in 2019, this number spiked significantly during the widespread lockdowns and social distancing measures prompted by the COVID-19 pandemic (Pabilonia and Redmond 2024). The authors further note that at its peak (April 2020), some major industries in the U.S. experienced increases of over 30 percentage points in remote work adoption. Similarly, according to Statistics Canada, while only about 7% of Canadians worked remotely in May 2016, this figure surged to approximately 40% by April 2020 (The Daily 2024). Since then, both countries have seen a gradual decline in remote work rates, yet hybrid work arrangements remain prevalent. In such setups, only a portion of total work hours are conducted on-site. In the U.S., employee preferences for hybrid work arrangements more than doubled compared to pre-pandemic levels, while employer demand for such arrangements nearly tripled (Tito 2025). In Canada, hybrid work is particularly common among public service providers (Gintova 2024). According to a recent global survey of college graduates, Canada leads the way, with an average of 1.9 days per week spent working from home (Aksoy et al. 2025).

An increasing number of studies emphasize the important role remote work plays for work-life balance, job satisfaction, productivity, office space optimization, talent attraction and retention, management complexity, and product or service innovation (Ferreira et al. 2021; Fang et al. 2025). Indeed, WFH can affect productivity and, consequently, firms' profits and wages. Since wages influence workers' standards of living, understanding the factors, including remote work, that affect them is crucial for economists.

In this paper, we theoretically examine the optimal level of remote work and its impact on firm profitability, and indirectly, wages. Using recent data from the Canadian Labour Force Survey (LFS), we empirically analyze the relationship between the percentage of firms reporting remote work arrangements by industry and its impact on wages, controlling for demographic and family factors, geographic location, and sector (public vs. private). Our main findings indicate that an increase in the industrial remote work intensity is associated with higher wages up to a certain threshold, beyond which the relationship reverses. This threshold varies significantly by industry. We also find stronger wage gains for parents of school-aged children, long-tenured employees, and full-time workers, whereas gender-dominated industries exhibit considerable rigidity.

From a theoretical standpoint, our model builds on key assumptions found in the frameworks of Bloom et al. (2015) and Davis et al. (2024). However, unlike these studies, we do not focus on employees' endogenous choice of employer. We assume that employers are aware that remote work can hurt profits, as employees might take more breaks while working from home. On the other hand, WFH can lower turnover and training costs and reduce the need for office space. We also assume that the productivity of remote work differs from that of in-office work. Total factor productivity (TFP) in the office increases with the number of in-office employees due to externalities brought by in-office interactions, and similarly, TFP in remote settings rises with the amount of remote work being performed. We consider two cases: Case 1: Remote employees only collaborate with other remote employees, and office employees collaborate only among themselves. Case 2: Remote and office employees can collaborate with each other.[5] If employees do not shirk excessively and if the management and operational complexities associated with remote work are minimal, then under Case 1, profit-maximizing firms prefer to delegate a fraction of their workforce to remote work. However, this choice is constrained by diminishing returns to productivity. Under Case 2, the more flexible collaboration between remote and on-site workers results in a higher share of remote employees. Thus, industries such as finance and insurance are more likely to support higher levels of WFH compared to sectors like trade, manufacturing, and retail. If increased profits ultimately translate into higher employee compensation, this theoretical framework helps explain our empirical findings, namely, that some industries have a higher remote work threshold beyond which the wage benefits decline, while in others, the effect is not statistically significant.

The rest of the paper is organized as follows. In the next section, we briefly review the literature on the effects of remote work on productivity and wages. Section 3 presents the theoretical model. Section 4 outlines the data, empirical methodology, and results. Section 5 discusses the main findings, while Section 6 outlines the additional heterogeneity analysis. The final section concludes.

2. Literature review

Most of the traditional economic literature relevant to our study examines how the transition to remote work affects productivity, profits and wages. Some studies attempt to estimate the effect of remote work on both productivity and employee compensation. While many important studies also examine other economic aspects of remote work, such as job satisfaction and employee turnover, this review focuses mainly on the ways remote work affects productivity, profitability, and wages.

Bloom et al. (2015) report the results of a nine-month randomized controlled trial on remote work conducted at one of the largest travel agencies in China. They found a 13% increase in employee performance among remote workers, driven by the greater convenience of being at home, improved worker satisfaction, and quieter home environment. Barrero et al. (2021) surveyed tens of thousands of working-age Americans across multiple waves and supplemented this data with informal interviews of business executives. Their findings suggest that the pandemic prompted experimentation with remote technologies and investment in related infrastructure, which led to improved perceptions of remote work productivity. A key prediction from the study is that the main source of productivity gains from remote work lies in the time saved from commuting. Bloom et al. (2024) conducted a six-month randomized controlled trial involving university graduates working in a technology company in China. They found that shifting to hybrid WFH saved commuting time and costs, improved flexibility and work satisfaction, reduced attrition, and led to improved employer perceptions of productivity gains. Choudhury et al. (2024) conducted a randomization experiment during the COVID-19 pandemic involving human-resource and microfinance employees in Bangladesh. They found that employees who spent an intermediate number of working days in the office achieved an optimal balance between flexibility and isolation. This balance resulted in greater work–life–balance satisfaction as well as higher quality work, products, and creativity. Fang et al. (2025) analyzed data from a stratified random

[5] We abstract from the no-collaboration scenario to maintain a balance between realism and brevity in the analysis of the average worker. Nonetheless, such scenarios can occur, particularly when there is a high proportion of new hires and recent immigrants, and they may strongly influence the productivity effects of remote work, warranting further investigation. We thank an anonymous referee for highlighting this issue. See Section 3 for further discussion.

survey of Canadian employers by industry, location, and firm size to assess the pandemic's impact on business operations, workplace practices, labor market dynamics, and organizational performance. One of the key takeaways is that remote work in the initial stages of the pandemic had a positive effect on organizational productivity, employee performance, and new product and service innovation. These outcomes may have resulted from the positive impact of the home environment on employee performance compared to traditional office settings, along with an increase in long-distance collaboration, despite potential challenges such as limited workspace, fewer opportunities for effective communication, and reduced in-person interactions that typically foster creativity. Pabilonia and Redmond (2024) studied 61 private industry sectors in the U.S. from 2019 to 2022 to examine whether TFP, measured as output relative to all inputs, was influenced by the share of remote workers. Accounting for pre-pandemic productivity trends, they concluded that greater remote-work adoption allowed firms to reduce their reliance on nonlabor inputs, and these cost savings ultimately contributed to TFP growth. However, this growth did not translate into higher compensation for workers over the two-year period; nonetheless, employees did benefit indirectly through reduced commute times and associated cost savings. Emanuel et al. (2023) analyzed performance of software engineers at a Fortune 500 firm. They found that while remote work had short-term positive effects on output by reducing the time senior engineers spent mentoring junior colleagues, it impeded long-term mentorship and skill development, particularly for junior employees and women. Furthermore, even a single remote team member was enough to notably reduce collaboration among co-located colleagues. Gibbs et al. (2023) used personnel and analytics data from a large Indian IT company to measure employee productivity before and during the pandemic lockdown. They concluded that while remote employees maintained roughly similar output levels, they had to work longer hours. As a result, output per worker dropped by 8% to 19%. The productivity loss was primarily attributed to increased communication, coordination, and collaboration costs associated with remote work. Burdett et al. (2024) used data from the UK Household Longitudinal Survey, which includes detailed questions on self-reported productivity since the pandemic began. The study found that workers in roles less suited to remote work, as well as women and low-income earners, experienced declines in productivity compared to the pre-pandemic period. One possible explanation is that, unless workplace conditions changed significantly during the pandemic, women, especially mothers, were disproportionately burdened with household tasks. In general, individuals with agreeable and conscientious personality traits adapt more effectively to different work environments than those with high cognition personality traits, resulting in differences in productivity. In industries where jobs require more physical contact, workers experienced productivity losses when shifting to the home environment. Larger firms appeared to adapt better to remote work, so their employees, on average, performed better at home.

Turning our attention to the studies concerning employee compensation, Golden and Eddleston (2020) analyzed individual-level survey data from 405 telecommuters and non-telecommuters, along with corporate data on promotions and salary growth. They concluded that there is no significant difference between the two groups in terms of promotions. However, extensive telecommuting was linked to fewer promotions and lower salary growth, likely because of the stigma surrounding flexible work. However, the presence of telecommuting normativeness, engagement in supplemental work, and having more direct contact with supervisors can reduce this stigma and even create advantages for telecommuters. Barrero et al. (2022), using monthly surveys of business executives on past wage growth and future wage expectations, found that the pandemic-driven shift to remote work increased the amenity value of work due to factors like reduction in commuting and grooming time. This improvement translated into a cumulative 2-percentage-point reduction in wage-growth pressure over a two-year period. Kouki and Sauer (2022) examined linked data on women and their children from the National Longitudinal Study of Youth. They found that remote work was associated with a decline in women's average hourly wages, a trend particularly pronounced among Black women. The authors attribute these findings to potential promotion bias, adverse task reassignments, and a decline in productive social interaction at the workplace. Arntz et al. (2022), using German household panel data, investigated gender and parenthood-related differences in remote work outcomes. They found that for childless employees, remote work was associated with more overtime hours but no wage gains. In contrast, parents, particularly mothers, experienced increased contractual hours and higher earnings. The authors suggest that cost savings from commuting, greater work flexibility, and more equitable sharing of childcare responsibilities, all factors especially relevant to mothers, help explain these findings. However, while fathers' wages increased following the uptake of remote work, mothers' wages remained stable unless they changed employers, possibly reflecting differences in bargaining power or gendered preconceptions. Pabilonia and Vernon (2022), using American Time Use Survey data from 2017–2018, showed that remote workers earned higher average wages than their office-based counterparts. However, mothers who primarily worked from home faced a wage penalty, likely due to more frequent interruptions during telework, which negatively affected their productivity. In a follow-up study, Pabilonia and Vernon (2025) analyzed American Community Survey data from 2010 to 2021. They found that remote workers, on average, earned more than onsite workers, except for blue-collar workers, who experienced a wage penalty that was only slightly reversed after 2020. White-collar workers received a notable wage premium for remote work during the pandemic, though the effects varied by race, disability status, and employment in government roles. Their results could be partly explained by the productivity-enhancing increase in sleep time for remote workers. However, again possibly due to frequent interruptions, women with children earned a slightly lower wage premium. Tito (2025), using data from the Current Population Survey, regressed U.S. wage growth on the share of remote workers relative to where it is technologically feasible (i.e., "remote work utilization") across states, industries, and occupations. The analysis concluded that, beginning in October 2022, there was no significant relationship between wage growth and remote work utilization over the following six months. These results appear to be driven by employees' preferences for workplace flexibility combined with firms' cost-saving incentives.

Our paper primarily relates to the second strand of the literature that focuses on the effect of WFH arrangements on wages. However, it also connects to the first strand, as a key component of our theoretical model and empirical hypothesis is that remote work can have a positive impact on productivity, and that this effect may vary across industries. To the extent that productivity gains translate into increased profits, we assume this will have a positive effect on wages. While it is true that higher firm profits do not necessarily result in increased employee compensation, we argue that any observed wage growth is at least partly attributable to productivity improvements driven by remote work.

3. Theoretical model

Following Bloom et al. (2015) and Davis et al. (2024), we assume that the actual number of hours worked full-time in the office is given by:

$$\bar{H} = b - B_o, \tag{1}$$

where $b > 0$ represents the total number of hours spent in the office, including break time, and $B_o > 0$ denotes the number of break hours per week. The actual number of remote hours worked is given as:

$$H(\theta) = b\theta - B(\theta), \tag{2}$$

where θ represents the fraction of the workweek spent working from home (i.e., remote work). Here $B(\theta) = \theta B_o + \gamma\theta B_o = (1+\gamma)\theta B_o$ represents the number of break hours during WFH periods, and $B(\theta = 0) = 0$. Thus, γ represents the shirking parameter, equal to the fraction of pre-WFH break hours that an employee adds to their break time when working remotely. If $\gamma > 0$, then $B'(\theta) > B_o$, i.e., a WFH employee shirks by taking extra break hours, $\gamma\theta B_o$. If $\gamma < 0$, remote employees are assumed to be hardworking, as they reduce break hours while working from home. This could occur because WFH employees save commuting time and may become more efficient in managing their schedules, potentially reducing break hours. They may have incentives to do so when, for example, they aim to improve their performance. Thus, $\gamma < 0$ or $B'(\theta) < B_o$ could help explain improved employee performance or higher productivity under WFH, as total output increases even when the reported hours, $\bar{H}$, remain constant.

In what follows, we consider two cases.

Case 1: Employees working from home collaborate only with other remote employees, while those working in the office collaborate exclusively with other on-site employees.

Following Davis et al. (2024), we assume that TFP of remote work is given by $A_h = \left(H(\theta)\right)^{\delta_h}$, where $\delta_h \in (0,1)$ captures the degree of externality associated with the aggregate amount of time spent working from home. This reflects a production externality in which working from home enhances interactions among remote workers, leading to greater learning spillovers, improved online coordination, and information sharing.

The output production function for remote work is given by:

$$Y_h(\theta) = A_h\left(H(\theta)\right)^{\alpha_h}, \tag{3}$$

where $\alpha_h \in (0,1)$ and $\delta_h + \alpha_h < 1$.

Next, following Davis et al. (2024), we assume that the TFP of working in the office is given by $A_o = \left((1-\theta)\bar{H}\right)^{\delta_o}$, where $\delta_o \in (0,1)$ captures the degree of externality from the aggregate amount of time spent working in the office. This reflects a externality due to people communicating and working physically nearby. The total number of hours worked in the office by an employee who adopts a mixed office–remote work arrangement is $(1-\theta)\bar{H}$. The output production function for on-site work is given by:

$$Y_o(\theta) = A_o\left((1-\theta)\bar{H}\right)^{\alpha_o}\left(k(\theta)\right)^{\beta}, \tag{4}$$

where $\alpha_o, \beta \in (0,1)$, $k(\theta)$ is the office space (complimentary input), and $k'(\theta) < 0$ since firms tend to reduce the amount of office space for fewer in-office hours.

Assume that the output produced by a single worker from home, Y_h, and the output produced from the office, Y_o, are perfect substitutes. Thus,

$$Y(\theta) = Y_h(\theta) + Y_o(\theta). \tag{5}$$

Firm's profit per employee is

$$\Pi(\theta) = Y(\theta) - \omega\bar{H} - ta(\theta) - rk(\theta) - \sigma\theta\bar{H}, \tag{6}$$

where $\omega\bar{H}$ is the labour cost, t is the recruiting and training cost per employee, $a(\theta)$ is the probability of an employee quitting with $a'(\theta) < 0$, r is the rental rate for office space, and $\sigma\theta\bar{H}$ denotes the total management complexity and operational costs associated with remote work. Here $\sigma > 0$ is a constant cost parameter.

Case 2: WFH employees collaborate with those working in the office.

Since all employees collaborate regardless of whether they work from home or the office, their TFP, A, is the same, i.e., $A \equiv A_h = A_o = (\bar{H})^{\delta}$. Because collaboration occurs independently of work location, TFP depends on $\bar{H}$ as if all employees were working full-time in the office. Thus, the production function for work-from-home becomes.

$$Y_h(\theta) = A\big(H(\theta)\big)^{\alpha_h}, \tag{3'}$$

and the production function of working at office becomes

$$Y_o(\theta) = A\big((1-\theta)\bar{H}\big)^{\alpha_o}\big(k(\theta)\big)^{\beta}. \tag{4'}$$

Firm's profit per employee follows expression (6). Next, following Bloom et al. (2015), we assume $a(\theta) \equiv \frac{1}{D+\theta}$, where $D > 1$ is a constant. Office space is given by $k(\theta) \equiv (1-\theta)K$, where $K > 0$ is a constant. Consequently, in the above two cases, we can compute an optimal θ^* such that $\Pi'(\theta) = 0$. First, let's plot the profit function for different values of θ. To do this, we need an estimate of γ. Aksoy et al. (2023) estimate that in Canada, time savings from working from home amount to 65 minutes per day, of which 41% is allocated to primary or secondary jobs. This corresponds to roughly 27 minutes per day, or approximately 2.2 hours over a standard 5-day workweek. Setting θ = 100% and $b = 40$ in Eq. (2), and letting $B_o = 5$, we obtain: $40 - 5(1+\gamma) = H$. If an employee is expected to work 35 hours but now effectively works 35 + 2.2 hours, we can set H = 37.2. Solving for γ gives $\gamma = -0.44$.[6] Next, for illustration, we set $D = 1.5$, $K = 1$, $\omega = 1$, $t = 0.1$, $r = 0.05$, $\sigma = 0.05$. We borrow some parameter values from Davis et al (2024): $\delta_h = \delta_o = 0.04$, $\alpha_h = \alpha_o = 0.67$, $\beta = 0.33$. Using the above parameter values, we plot the profit function in Figure 1 for different cases as a function of θ.[7]

[6] These numbers also confirm the evidence that employees who work from home tend to work longer hours. For example, Gibbs et al. (2021) report on a study discussed in *The Economist* that uses data from thousands of employees at an Asian technology company where tracking applications were installed to monitor online activity. The results show that employees working from home performed about 30 percent more work. Similar evidence is reported by Visé (2024). We thank an anonymous referee for bringing this evidence to our attention.

[7] This result helps explain why some firms are willing to offer a portion of the workweek to be performed remotely and why a strong willingness to pay for working from home does not mechanically imply lower wages for remote

[**Figure 1 here**]

Using the same parameters, we plot θ^* against γ values in Figure 2 for both Case 1 and Case 2.

[**Figure 2 here**]

A positive θ^* indicates that an increase in the share of remote employees is associated with a higher profit up to a certain threshold, beyond which the relationship reverses. This is because remote work contributes to virtual production externalities and reduces monetary outlays for office space, as well as turnover costs. However, these benefits come at the expense of in-person contact externalities typically found in office settings. Remote work may also lead to increased shirking, higher management and coordination costs, and a reduction in the benefits of complementary office inputs. Figure 2 shows that in both scenarios, the less remote workers shirk, the more profitable it becomes for the firm to delegate part of its workforce to WFH. In Case 2, where remote work does not reduce the productivity of in-office workers, the firm prefers to hire more remote employees compared to Case 1. This leads to a testable hypothesis: industries in which remote workers are likely to maintain their productivity and effective communication are more likely to adopt remote work practices. This, in turn, can result in higher firm profits and, indirectly, higher wages for remote workers.

It is worth noting that while our analysis of Case 1 and Case 2 focuses on collaboration structures typical of most work environments, some settings involve employees working from home with very limited collaboration. This corresponds to Case 1 with δ_h equal to zero. Such situations are more likely for new hires and recent immigrants, who often lack established professional networks and rely on informal, in-person interactions to integrate into the workplace and acquire firm-specific knowledge. In these contexts, remote work may substantially reduce effective collaboration, approaching the extreme case of minimal interaction among employees working from home. Workforce composition, particularly the share of new hires and recent immigrants, may therefore be an important determinant of the productivity effects of remote work and deserves further investigation.[8]

4. Data and empirical strategy

4.1 Data and variables

In this paper we combine two different data sources from Statistics Canada. The first is the Labour Force Survey (LFS), a monthly survey measuring the current state of the Canadian labour market that was used, among other things, to calculate the national, provincial, territorial and regional employment and unemployment rates. It is a nationally representative survey in Canada. The second is the anticipated change in levels of remote work over the next 12 months, categorized by the North American Industry Classification System (NAICS). The LFS covers detailed survey questions on employment and unemployment, hours of work and work arrangements, industries and occupations,

workers. As shown by Cullen et al. (2025), wages need not be lower when productivity gains, worker sorting, or firm-side frictions offset the implied compensating differential. Similarly, Bartik et al. (2024) document that firms' perceived productivity of remote work shifted from negative early in the pandemic to positive thereafter. We thank the anonymous referee for bringing these observations to our attention.

[8] We thank an anonymous referee for highlighting this issue.

unionization and industrial relations, as well as wages, salaries, and other earnings. The period of the second dataset spans from the first quarter of 2023 to the first quarter of 2024.

Our dependent variable is the logarithm of usual hourly wages for the workers surveyed in the LFS. The key explanatory variable (*remotepercent or percentage of remote workers by industry*) is the percentage of firms who reported 100% of employees having at least some remote work. The term *remotesqr* represents the squared term of *remotepercent*. It is included in wage regressions to capture nonlinear relationships between remote work intensity and wages. Without this term, the model would assume a strictly linear effect, where each 1% increase in remote work proportionally and identically affects wages at all levels. Yet economic phenomena often exhibit diminishing returns, threshold effects, or turning points. The negative coefficient observed for *remotesqr* suggests that the initial positive wage gains from remote work peak and eventually reverse as remote work in the industry becomes widespread.

Our control variables in the wage equation are the conventional ones utilized in the literature. We use education as a proxy for human capital, as well as age, gender, marital status, and child status for personal and family characteristics. Provincial controls are also incorporated. For those who are employed, the control variables also include additional job characteristics (multiple-job holder status, public-private sector status, part-time employment status, temporary employment status, tenure, union membership status, and firm size). Our regression results for the control variables are generally in the expected direction and consistent with the literature. Summary statistics are given in Table 1 (see Appendix B).

[**Table 1 here**]

4.2 Empirical model

The rapid increase of remote work during the COVID-19 pandemic, while being initially unavoidable, revealed important gaps in our understanding of its long-term economic implications, its nonlinear relationship with wages and heterogeneous industry effects. Previous theoretical literature emphasized that remote productivity depends on balancing the externalities arising from working from home against those generated by in-office interactions, yet empirical validation of the theorized inverted U-shaped wage effect remained scarce. Concurrently, emerging evidence (Pabilonia and Vernon 2025; Jiang et al. 2024) highlighted stark industry disparities: digitally intensive sectors (e.g., finance) reaped wage gains, while manual labor-intensive industries (e.g., construction) struggled to translate remote adoption into productivity and wage growth. Critically, serious endogeneity issues arise, such as the self-selection of productive workers into remote roles (Hsu and Tambe 2025), while pandemic-induced productivity shocks risked confounding observational estimates. To address these gaps, we leverage Canadian Labour Force Survey data (2023–2024Q1) to: (1) Test the theoretical inflection point by modeling wages as a quadratic function of industry remote worker share (*remotepercent* and *remotesqr*), (2) Disentangle industry heterogeneity through stratified regressions, (3) Address endogeneity concerns using lagged industry-level remote-work intensity and its square as instruments, where lagged remote-work patterns shaped by pre-existing technological conditions and pandemic-related adjustments satisfy the exclusion restriction by affecting current wages only through current remote-work intensity.

In our baselines scenario, we estimate the following equation via ordinary least squares (OLS) estimator:

$$\begin{aligned}\text{lnwage}_{it} = \beta_0 + \beta_1 \text{remotepercent}_{ijt} + \beta_2 \text{remotesqr}_{ijt} + \beta_3 \text{X}_{it} + \alpha_q \\ + \epsilon_{it}\end{aligned} \tag{7}$$

where i represents individual workers, j indicates industries, t represents quarters, α_q and ϵ_{it} represent quarterly fixed effect, and idiosyncratic error term, respectively. Given the key explanatory variable remote work intensity is measured at the industry level, rather than individual level for the unit of analysis, standard errors are clustered at industry level to avoid biased inferences.[9]

However, OLS poses several econometric challenges because the percentage of firms who choose remote work arrangement may not be random, and the non-exogeneity of percentage of working remotely could potentially introduce bias to the estimation results. It has been suggested that endogeneity could be due to, for example, factors that simultaneously affect both remote work intensity and productivity of workers, or from unobserved firm heterogeneity.

Endogeneity in the relationship between remote work arrangement and wages arises from three interconnected sources. First, simultaneous external shocks, such as technological disruptions or pandemics, may concurrently increase remote work adoption and alter worker productivity (e.g., COVID-19 lockdowns accelerated remote work while disrupting supply chains, thereby lowering wages). Second, unobserved firm heterogeneity affecting self-selection. Third, reverse causality emerges when firm performance influences both variables. That is, profitable firms may proactively invest in remote infrastructure while offering higher wages, creating a spurious relationship between wages and remote work adoption. Taken together, these factors violate exogeneity assumptions, biasing OLS estimates and necessitating an instrumental variable to address endogeneity concerns.

The lagged industry-level remote-work intensity is used as the primary instrumental variable (IV), and its squared term is included as an additional instrument (IV_2) to match the quadratic specification in the second stage. These instruments are plausibly exogenous because lagged remote-work intensity captures earlier industry-level adoption patterns shaped by sudden lockdown policies and technological conditions such as pre-exisiting broadband capacity, organizational practices, and the broader adjustments associated with the pandemic period, rather than contemporaneous individual wage determination. Through technological and organizational inertia, lagged remote-work intensity strongly predicts current remote-work intensity, while its squared term provides the corresponding variation needed for the non-linear specification. Conditional on the rich set of individual controls, job

[9] We acknowledge the following limitations of our study. First, while the theoretical framework is developed at the firm level, the empirical analysis is conducted at the industry level. As a result, the estimated coefficients should be interpreted as capturing average effects across industries rather than firm-level responses. Second, our measure of remote-work intensity uses industry-level proxy, rather than the actual share of hours worked remotely by employees. Therefore, this variable should be interpreted as a proxy for the prevalence of remote work. We further clarify that our identification relies on cross-industry variation in remote-work intensity. Accordingly, the estimated effects should be interpreted as reflecting differences in wage outcomes across industries with varying exposure to remote work, rather than causal effects at the individual level. We would like to thank an anonymous referee and the Editor for bringing these issues to our attention.

characteristics, and time effects, the remaining direct effect of these lagged measures on current wages is limited. This supports both the relevance and exclusion restrictions required for valid instruments.

5. Results and discussions

In this section, we briefly discuss the results of our baseline estimation. The first column of Table 2 shows the results of OLS estimations. The coefficient for *remotepercent* is 1.094, which is statistically significant at the 1% level (indicated by three asterisks, ***). This suggests that for every 1% increase in the percentage of industrial remote work intensity, there is an average increase of 1.094% in wages, holding all other factors constant. The coefficient for *remotesqr* is -0.856, also statistically significant at the 1% level. This negative coefficient indicates that the relationship between remote work intensity and wages is not linear. As the remote work intensity increases, the initial positive effect on wages diminishes, and beyond a certain point, further increases in remote work percentage could lead to a decrease in wages. The positive wage effect diminishes and turns negative when remote work intensity exceeds 63.9%.[10] Rather than interpreting these coefficients in isolation, the quadratic specification implies that the marginal effect of remote work is given by $\beta_1 + 2\beta_2 X$. Evaluated at the sample mean of remote-work intensity, the marginal effect is 0.690, as reported in Table 2. This implies that a 10-percentage-point increase in remote-work intensity is associated with approximately a 0.0690 increase in log wages at the mean.

[**Table 2 here**]

Column (2) presents the IV results. The linear term *remotepercent* carries a coefficient of 1.517 (significant at the 1% level), while the coefficient on the squared remotepercent is –1.457 (likewise 1% significant). These estimates imply that the wage premium rises only up to a remote-work intensity level of about 52.1% and declines thereafter, mirroring the inverted-U shape. First-stage F-statistics and the endogeneity test are significant at the 1% level, attesting to the strength of the instruments and the appropriateness of the IV approach. Evaluated at the sample mean of remote-work intensity, the marginal effect of the IV remote variable is 0.830, as reported in Table 2.

The first-stage results further indicate that the excluded instruments are strongly correlated with the endogenous regressors. Specifically, both IV and IV_2 are positive and statistically significant in the first-stage regressions for Remotepercent and Remotesqr, supporting instrument relevance. In addition, the first-stage F-statistics are well above conventional thresholds, and the endogeneity test rejects the null that the regressors are exogenous, confirming both the strength of the instruments and the appropriateness of the IV approach.

6. Heterogeneity analysis

To enhance our understanding of the relationship between remote work and wages, it is crucial to conduct a heterogeneity analysis across different industries. Such an analysis allows us to recognize that the impact of remote work on wages is not uniform across all sectors. Instead, it might vary

[10] We compute this using the inverted U-shaped relationship formula, where the threshold value (i.e., the inflection point at which the wage effect shifts from positive to negative) is calculated as $-\beta_1/(2\beta_2)$.

significantly due to differences in industry characteristics, the nature of production, and adaptability to remote work arrangements.

Firstly, the nature of tasks within an industry determines the feasibility and effectiveness of remote work. For instance, industries like finance and insurance, which rely heavily on digital technology and information processing, are more adaptable to remote work. This adaptability can enhance productivity and, consequently, wages. On the other hand, industries such as agriculture and manufacturing, which involve substantial manual labor and on-site operations, have limited potential for remote work, leading to weaker or even negative effects on productivity, therefore, wages. Secondly, the productivity gains from remote work differ across industries. In some sectors, remote work can reduce commuting time, increase work flexibility, and improve work-life balance, thereby boosting employees' productivity. In contrast, in other industries, the lack of face-to-face interaction and supervision may lead to decreased productivity and wage stagnation or decline. Lastly, the competitive environment and labor market dynamics within each industry also play a crucial role. Industries with high competition may adopt remote work to attract and retain talent, leading to increased wages. Conversely, industries with low competition may not experience the same wage pressures. By examining the industry-specific effects of remote work on wages, we can provide more targeted and effective policy recommendations. This analysis helps policymakers and business leaders understand the optimal levels of remote work for different industries, ensuring that remote work policies enhance productivity and wages without causing efficiency losses. It also aids in identifying industries that may require additional support or resources to effectively implement remote work arrangements.

[**Table 3A here**]

[**Table 3B here**]

[**Table 3C here**]

In agriculture, forestry, fishing and hunting, mining and oil and gas extraction, and construction, the coefficients on both remotepercent and remotesqr are statistically insignificant, providing no robust evidence that remote-work intensity affects wages in these industries (Table 3A). By contrast, manufacturing displays a clear and statistically significant inverted-U relationship: the coefficient on remotepercent is positive and significant, while the coefficient on remotesqr is negative and significant, indicating that remote work is initially associated with higher wages in manufacturing, but that this positive effect diminishes as remote-work intensity rises. In wholesale trade, the coefficients are not statistically significant at conventional levels.

.In retail trade, transportation and warehousing, information and cultural industries, and finance and insurance, the coefficients on both remotepercent and remotesqr are not statistically significant at conventional levels (Table 3B). In contrast, real estate and rental and leasing exhibits a statistically significant U-shaped relationship: the coefficient on remotepercent is negative and significant, while the coefficient on remotesqr is positive and significant.

In professional, scientific and technical services, accommodation and food services, and other services except public administration, the coefficients on both remotepercent and remotesqr are not statistically significant (Table 3C). By contrast, two service sectors exhibit statistically significant inverted-U relationships. In admin and support, waste management and remediation services, the coefficient on remotepercent is positive and significant, while the coefficient on remotesqr is negative and significant. A similar pattern appears in health care and social assistance, with a positive linear term and a negative quadratic term.

.Overall, the heterogeneous estimates show that statistically significant wage effects of remote work are concentrated in specific industries. Manufacturing, admin and support services, and health care and social assistance exhibit an inverted-U relationship, while real estate and rental and leasing show a U-shaped pattern. In the remaining industries, the coefficients are not statistically significant, providing no evidence of a systematic wage effect.

To further examine whether the wage effect of remote work differs systematically across industries, Table 4 classifies industries into digital-intensive and non-digital-intensive industry groups and introduces interaction terms between the digital-industry indicator and both the linear and quadratic terms of remote-work intensity. The results reveal substantial heterogeneity.

The estimated coefficients on the linear and quadratic terms are 2.845 and -5.824, respectively, suggesting that remote work is initially associated with higher wages in non-digital sectors, but that the marginal benefit declines as remote-work intensity rises. The interaction terms are both highly significant, implying that the wage effects of remote work differ markedly in digital-intensive industries from non-digital-intensive industries. The coefficient on remote_digital is -7.383, while the coefficient on remote2_digital is 11.122, indicating that, relative to non-digital-intensive industries, the wage–remote work relationship in digital-intensive sectors is weaker at lower levels of remote-work intensity and follows a non-linear pattern. In addition, the coefficient on the digital dummy is positive and significant, suggesting that workers in digital-intensive industries earn higher wages on average, conditional on other observed characteristics. Overall, these findings provide further evidence that the wage implications of remote work depend importantly on industry digital intensity, and that the economic effects of remote-work adoption are far from uniform across sectors.

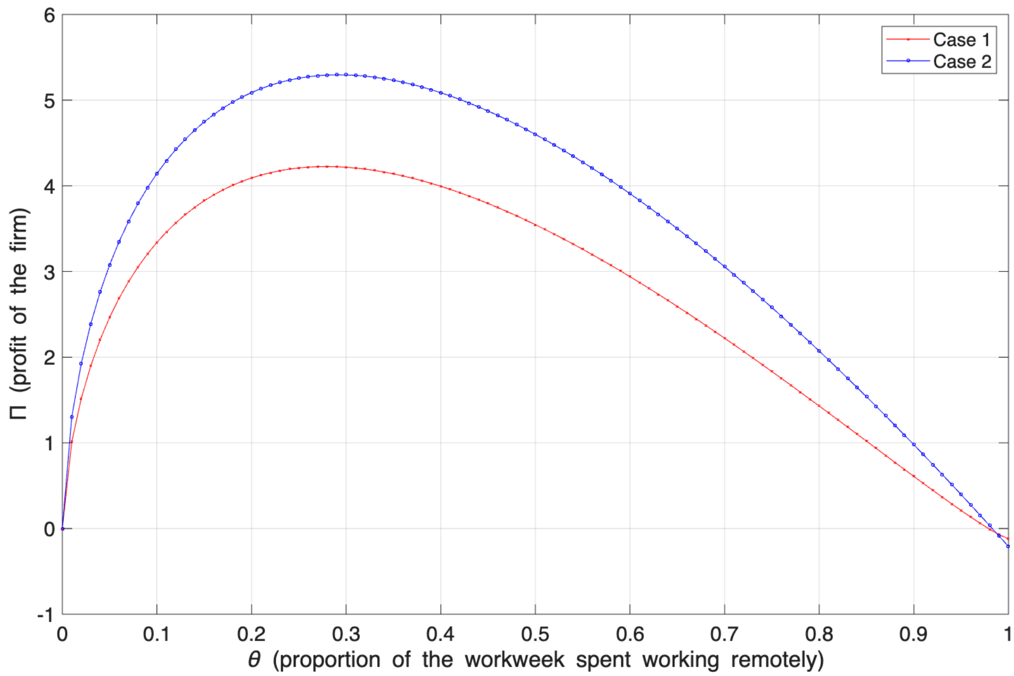
7. Conclusions

Building on the seminal contributions of Bloom et al. (2015) and Davis et al. (2024), we develop a simple theoretical model of WFH that incorporates remote work and in-office externalities, cost savings from remote work, and the potential inefficiencies arising from its excessive adoption. A key feature of the model is the assumption that both productivity and firm profitability vary with the share of firms with remote work arrangements by industry. We examine two scenarios: Case 1: Remote and in-office workers collaborate only within their respective groups. Case 2: Cross-group collaboration is allowed, enhancing the feasibility and benefits of remote work. The model links WFH-induced productivity changes to firm profitability and, by extension, to wages. This framework provides a theoretical basis for an inverted U-shaped relationship between the share of remote work firms across industry and wages.

Empirically, we use data from the Canadian Labour Force Survey to estimate the relationship between industry-level remote work intensity and individual wages. Our findings, based on baseline estimates as well as robustness and heterogeneity analyses, highlight significant variation across industries and demographic groups. Overall, the results support the hypothesis that wages increase with remote work intensity up to a threshold (approximately 52.1–63.9%), after which they begin to decline. These findings have important policy implications. They suggest the need to design optimal guidelines and supportive infrastructure for remote work, tailored to the characteristics of specific industries, regions, and demographic groups. Doing so could help maximize productivity and wage gains while mitigating potential negative effects, such as increased management complexity or reduced collaboration, and could also influence earnings inequality across sectors and populations.

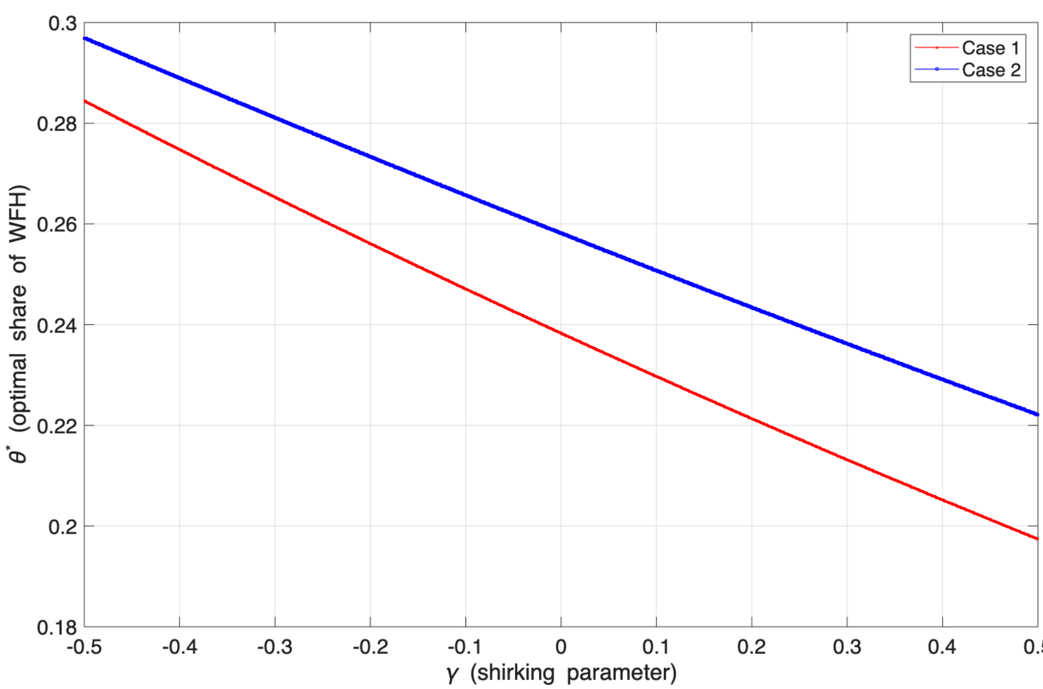
Appendix A

Figure 1: Inverted U-Shaped Relationship Between Firm Profits and the Share of Remote Work



Note: To scale the profit values into the positive range, we multiply the right-hand side of equation (5) by the parameter $\bar{A} = 2.8134$.

Figure 2: Optimal Remote Work as a Function of Employee Shirking



Note: A negative value of γ implies that remote workers work harder than when they are in the office.

Appendix B

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min	Max	N
Lnwage	3.385	.47	1.53	5.377	733396
remotepercent	.236	.115	.058	.567	733396
Remotesqr	.069	.068	.003	.321	733396
IV	.241	.117	.058	.567	733396
IV_2	.072	.07	.003	.321	733396
[Male]	.51	.5	0	1	733396
Female	.49	.5	0	1	733396
[Married]	.462	.499	0	1	733396
Living in common law	.152	.359	0	1	733396
Widowed	.011	.103	0	1	733396
Separated	.025	.158	0	1	733396
Divorced	.042	.201	0	1	733396
Single, never married	.307	.461	0	1	733396
[0 to 8 years]	.012	.107	0	1	733396
Some secondary	.066	.249	0	1	733396
Gr 11 to 13, graduate	.182	.386	0	1	733396
Some post secondary	.053	.224	0	1	733396
Post secondary certificate	.364	.481	0	1	733396
University: bachelors degree	.219	.413	0	1	733396
University: graduate degree	.105	.306	0	1	733396
[Age 15 to 19]	.053	.225	0	1	733396
Age 20 to 24	.082	.275	0	1	733396
Age 25 to 29	.097	.295	0	1	733396
Age 30 to 34	.108	.311	0	1	733396
Age 35 to 39	.112	.316	0	1	733396
Age older than 40	.547	.498	0	1	733396
[Youngest child less than 6 years]	.115	.319	0	1	733396

Youngest child 6 to 12	.115	.319	0	1	733396
Youngest child 13 to 17	.072	.258	0	1	733396
Youngest child older than 18	.699	.459	0	1	733396
[British Columbia]	.116	.32	0	1	733396
Newfoundland	.043	.203	0	1	733396
Prince Edward Island	.023	.15	0	1	733396
Nova Scotia	.046	.209	0	1	733396
New Brunswick	.048	.214	0	1	733396
Quebec	.184	.387	0	1	733396
Ontario	.322	.467	0	1	733396
Manitoba	.074	.263	0	1	733396
Saskatchewan	.061	.24	0	1	733396
Alberta	.082	.275	0	1	733396
[Nonunion mem]	.682	.466	0	1	733396
Union mem	.318	.466	0	1	733396
[Full time]	.83	.376	0	1	733396
Part time	.17	.376	0	1	733396
[Permanent]	.884	.32	0	1	733396
Temp	.116	.32	0	1	733396
[Single job]	.944	.23	0	1	733396
Multiple job	.056	.23	0	1	733396
[Private employee]	.735	.442	0	1	733396
Public employee	.265	.442	0	1	733396
Tenure	7.376	6.922	.083	20	733396

Note(s): Variables enclosed in brackets [ ] are used as the reference category in the regressions.

Table 2: Estimation results using OLS and IV estimator

VARIABLES	OLS		IV			
			First stage		Second stage	
	lnwage	marginal effects	Remotepercent	Remotesqr	lnwage	marginal effects
Remotepercent	1.094***	0.690			1.517***	0.830
	(0.147)				(0.321)	
Remotesqr	-0.856***				-1.457***	
	(0.263)				(0.553)	
IV			0.664***	0.057***		
			(0.019)	(0.013)		
IV_2			0.340***	0.768***		
			(0.026)	(0.017)		
Male	Ref.					
Female	-0.149***		-0.002***	-0.001***	-0.150***	
	(0.010)		(0.000)	(0.000)	(0.009)	
Married	Ref.					
Living in common law	0.033***		-0.000	0.000	0.033***	
	(0.004)		(0.000)	(0.000)	(0.004)	
Widowed	-0.095***		-0.001	-0.000	-0.095***	
	(0.009)		(0.001)	(0.001)	(0.009)	
Separated	-0.036***		-0.001	-0.001**	-0.037***	
	(0.003)		(0.001)	(0.000)	(0.003)	
Divorced	-0.023***		0.000	-0.000	-0.023***	
	(0.003)		(0.001)	(0.000)	(0.003)	
Single, never married	-0.033***		-0.001*	0.000**	-0.033***	
	(0.007)		(0.000)	(0.000)	(0.007)	
0 to 8 years	Ref.					
Some secondary	0.065***		-0.002***	-0.001**	0.064***	
	(0.018)		(0.000)	(0.000)	(0.017)	
Gr 11 to 13, graduate	0.101***		-0.001	-0.000	0.099***	
	(0.012)		(0.000)	(0.000)	(0.011)	
Some post secondary	0.161***		0.001***	0.001***	0.158***	

	(0.023)	(0.000)	(0.000)	(0.021)
Post secondary certificate	0.227***	0.000	0.000	0.223***
	(0.013)	(0.000)	(0.000)	(0.012)
University: bachelors degree	0.388***	0.007***	0.004***	0.383***
	(0.018)	(0.000)	(0.000)	(0.017)
University: graduate degree	0.501***	0.009***	0.005***	0.495***
	(0.019)	(0.001)	(0.001)	(0.018)
Age 15 to 19	Ref.			
Age 20 to 24	-0.007	-0.002***	-0.001*	-0.010**
	(0.005)	(0.000)	(0.000)	(0.004)
Age 25 to 29	0.075***	-0.000	-0.000	0.070***
	(0.009)	(0.000)	(0.000)	(0.007)
Age 30 to 34	0.145***	0.001***	0.001***	0.139***
	(0.008)	(0.000)	(0.000)	(0.007)
Age 35 to 39	0.167***	0.001	0.000	0.160***
	(0.011)	(0.001)	(0.000)	(0.011)
Age older than 40	0.157***	0.001***	0.000**	0.151***
	(0.006)	(0.000)	(0.000)	(0.005)
Youngest child less than 6 years	Ref.			
Youngest child 6 to 12	-0.007	0.001**	0.001*	-0.007
	(0.008)	(0.000)	(0.000)	(0.007)
Youngest child 13 to 17	0.004	0.001**	0.000	0.004
	(0.007)	(0.000)	(0.000)	(0.007)
Youngest child older than 18	-0.066***	0.001***	0.001***	-0.065***
	(0.006)	(0.000)	(0.000)	(0.006)
British Columbia	Ref.			
Newfoundland	-0.133***	-0.003***	-0.001***	-0.132***
	(0.003)	(0.000)	(0.000)	(0.003)
Prince Edward Island	-0.186***	-0.003***	-0.001***	-0.185***
	(0.001)	(0.000)	(0.000)	(0.001)
Nova Scotia	-0.176***	-0.001***	-0.001***	-0.175***

	(0.001)	(0.000)	(0.000)	(0.001)
New Brunswick	-0.178***	-0.002***	-0.001***	-0.178***
	(0.002)	(0.000)	(0.000)	(0.002)
Quebec	-0.071***	0.001***	0.000***	-0.071***
	(0.002)	(0.000)	(0.000)	(0.002)
Ontario	-0.038***	0.001***	0.000***	-0.038***
	(0.001)	(0.000)	(0.000)	(0.001)
Manitoba	-0.152***	-0.000***	-0.001***	-0.152***
	(0.001)	(0.000)	(0.000)	(0.002)
Saskatchewan	-0.103***	-0.000**	-0.000***	-0.103***
	(0.002)	(0.000)	(0.000)	(0.002)
Alberta	0.000	0.001***	0.000	-0.001
	(0.002)	(0.000)	(0.000)	(0.002)
Nonunion	Ref.			
Union	-0.001	-0.003***	-0.003***	-0.002
	(0.007)	(0.000)	(0.000)	(0.006)
Parttime	Ref.			
Fulltime	0.167***	0.005***	0.002***	0.164***
	(0.007)	(0.000)	(0.000)	(0.007)
Temp	Ref.			
Permanent	0.073***	-0.003***	-0.001***	0.075***
	(0.011)	(0.000)	(0.000)	(0.010)
Multiple Jobs	Ref.			
Single Job	0.053***	-0.000	0.000	0.054***
	(0.010)	(0.000)	(0.000)	(0.009)
Private Employee	Ref.			
Public Employee	0.136***	-0.002***	-0.005***	0.129***
	(0.012)	(0.000)	(0.000)	(0.014)
Tenure	0.012***	0.000**	0.000	0.012***
	(0.001)	(0.000)	(0.000)	(0.001)
First Quarter	-0.019***	0.019***	0.014***	-0.021***
	(0.002)	(0.001)	(0.001)	(0.002)

Second Quarter	-0.028***	0.013***	0.008***	-0.029***
	(0.003)	(0.001)	(0.001)	(0.002)
Third Quarter	-0.022***	0.033***	0.026***	-0.021***
	(0.002)	(0.002)	(0.001)	(0.003)
Constant	2.644***	0.030***	-0.012***	2.597***
	(0.030)	(0.003)	(0.002)	(0.040)
F-statistics(remotepercent)				686961***
F-statistics (remotesqr)				187413***
Tests of endogeneity				38.9897***
Partial R-sq.				0.7742
Observations	733,396	733,396	733,396	733,396
R-squared	0.412	0.793	0.793	0.411

Note(s): Significance at:***p<0.01;**p<0.05;*p<0.1. ‘Ref.’ indicates the reference group, which represents the baseline category in the regression table. Weighted regression models. Standard errors in parentheses are clustered at industry level. Controls include individual characteristics and additional job characteristics.
Source(s): Authors’ own work

Table 3A: Heterogeneity estimation results

	(1)	(2)	(3)	(4)	(5)
	Agriculture, forestry, fishing and hunting	Mining, quarrying, and oil and gas extraction	Construction	Manufacturing	Wholesale trade
VARIABLES	lnwage	lnwage	lnwage	lnwage	lnwage
remotepercent	-1.456	0.240	-2.027	1.283**	13.808
	(2.490)	(0.851)	(1.458)	(0.403)	(7.870)
remotesqr	7.217	-0.292	6.849	-3.038**	-29.658
	(11.724)	(1.732)	(3.908)	(1.147)	(16.760)

Table 3B: Heterogeneity estimation results

	(1)	(2)	(3)	(4)	(5)
	Retail trade	Transportation and warehousing	Information and cultural industries	Finance and insurance	Real estate and rental and leasing
VARIABLES	lnwage	lnwage	lnwage	lnwage	lnwage
remotepercent	-0.785	3.380	-3.543	-6.377	-13.525**
	(0.503)	(2.279)	(2.768)	(5.839)	(4.546)
remotesqr	2.036	-6.129	3.444	8.408	16.631**
	(1.600)	(3.866)	(2.858)	(8.093)	(5.636)

Table 3C Heterogeneity estimation results

	(1)	(2)	(3)	(4)	(5)
	Professional, scientific and technical services	Admin & support, waste mgnt and remediation services	Health care and social assistance	Accommodation and food services	Other services (except public admin)
VARIABLES	lnwage	lnwage	lnwage	lnwage	lnwage
remotepercent	-0.569	14.584***	18.512***	1.481	-3.650
	(1.564)	(1.867)	(3.680)	(1.037)	(2.364)
remotesqr	0.500	-33.189***	-42.026***	-6.823	7.039
	(1.514)	(4.254)	(8.351)	(5.333)	(4.472)

Note(s): Significance at:***p<0.01;**p<0.05;*p<0.1
Weighted regression models. Standard errors in parentheses are clustered at industry level. Controls include individual characteristics and additional job characteristics
Source(s): Authors' own work

Table 4 Heterogeneity estimation results

VARIABLES	(1)
	Lnwage
remotepercent	2.845***
	(0.127)
remotesqr	-5.824***
	(0.202)
digital	1.411***
	(0.096)
remote_digital	-7.383***
	(0.396)
remote2_digital	11.122***
	(0.268)
Constant	2.396***
	(0.034)
Observations	733,396
R-squared	0.418

Note(s): Significance at:***p<0.01;**p<0.05;*p<0.1. 'Ref.' indicates the reference group, which represents the baseline category in the regression table. Weighted regression models. Standard errors in parentheses are clustered at industry level. Controls include individual characteristics and additional job characteristics.
Source(s): Authors' own work

Appendix C

Table 1: Summary Statistics

Variable	N	Mean	Std. Dev.	Min	Max
Lnwage	694259	3.417	.459	1.53	5.377
remotepercent	694259	.239	.114	.058	.567
Remotesqr	694259	.07	.068	.003	.321
IV	694259	.244	.115	.058	.567
IV_2	694259	.073	.07	.003	.321
[Male]	694259	.51	.5	0	1
Female	694259	.49	.5	0	1
[Married]	694259	.488	.5	0	1
Living in common law	694259	.16	.367	0	1
Widowed	694259	.011	.106	0	1
Separated	694259	.027	.162	0	1
Divorced	694259	.045	.207	0	1
Single, never married	694259	.269	.443	0	1
[0 to 8 years]	694259	.011	.103	0	1
Some secondary	694259	.043	.202	0	1
Gr 11 to 13, graduate	694259	.176	.381	0	1
Some post secondary	694259	.047	.211	0	1
Post secondary certificate	694259	.382	.486	0	1
University: bachelors degree	694259	.231	.422	0	1
University: graduate degree	694259	.111	.314	0	1
[Age 20 to 24]	694259	.087	.282	0	1
Age 25 to 29	694259	.102	.303	0	1
Age 30 to 34	694259	.114	.318	0	1
Age 35 to 39	694259	.119	.323	0	1
Age older than 40	694259	.578	.494	0	1

[Youngest child less than 6 years]	694259	.121	.326	0	1
Youngest child 6 to 12	694259	.121	.326	0	1
Youngest child 13 to 17	694259	.076	.265	0	1
Youngest child older than 18	694259	.682	.466	0	1
[British Columbia]	694259	.117	.321	0	1
Newfoundland	694259	.043	.204	0	1
Prince Edward Island	694259	.023	.15	0	1
Nova Scotia	694259	.046	.21	0	1
New Brunswick	694259	.048	.214	0	1
Quebec	694259	.181	.385	0	1
Ontario	694259	.323	.468	0	1
Manitoba	694259	.074	.262	0	1
Saskatchewan	694259	.061	.24	0	1
Alberta	694259	.082	.275	0	1
[Nonunion mem]	694259	.67	.47	0	1
Union mem	694259	.33	.47	0	1
[Permanent]	694259	.897	.304	0	1
Temp	694259	.103	.304	0	1
[Single job]	694259	.944	.231	0	1
Multiple job	694259	.056	.231	0	1
[Private employee]	694259	.723	.447	0	1
Public employee	694259	.277	.447	0	1
Tenure	694259	7.726	6.946	.083	20

Note(s): Variables enclosed in brackets [ ] are used as the reference category in the regressions.

Table 2: Estimation results using OLS and IV estimator

VARIABLES	OLS		IV			
			First stage		Second stage	
	lnwage	marginal effects	Remotepercent	Remotesqr	lnwage	marginal effects
Remotepercent	1.169***	0.721			1.605***	0.862
	(0.160)				(0.340)	
Remotesqr	-0.937***				-1.554***	
	(0.285)				(0.582)	
IV			0.665***	0.052***		
			(0.021)	(0.013)		
IV_2			0.332***	0.774***		
			(0.029)	(0.019)		
Male	Ref.					
Female	-0.157***		-0.002***	-0.001***	-0.157***	
	(0.010)		(0.000)	(0.000)	(0.010)	
Married	Ref.					
Living in common law	0.033***		-0.000	0.000	0.033***	
	(0.005)		(0.000)	(0.000)	(0.004)	
Widowed	-0.091***		-0.002*	-0.000	-0.090***	
	(0.009)		(0.001)	(0.001)	(0.009)	
Separated	-0.036***		-0.001	-0.001**	-0.036***	
	(0.003)		(0.001)	(0.000)	(0.003)	
Divorced	-0.021***		0.000	-0.000	-0.022***	
	(0.003)		(0.001)	(0.000)	(0.003)	
Single, never married	-0.033***		0.000	0.000**	-0.033***	
	(0.007)		(0.000)	(0.000)	(0.007)	
0 to 8 years	Ref.					
Some secondary	0.067***		-0.001	-0.001	0.066***	
	(0.015)		(0.001)	(0.001)	(0.013)	
Gr 11 to 13, graduate	0.115***		0.001	0.000	0.113***	
	(0.011)		(0.001)	(0.000)	(0.010)	

Some post secondary	0.183***	0.000	0.000	0.180***
	(0.022)	(0.001)	(0.001)	(0.020)
Post secondary certificate	0.240***	0.002***	0.001**	0.236***
	(0.011)	(0.001)	(0.000)	(0.010)
University: bachelors degree	0.401***	0.007***	0.004***	0.394***
	(0.018)	(0.001)	(0.000)	(0.017)
University: graduate degree	0.513***	0.009***	0.006***	0.506***
	(0.020)	(0.001)	(0.000)	(0.019)
Age 20 to 24	Ref.			
Age 25 to 29	0.079***	0.002***	0.000**	0.077***
	(0.004)	(0.000)	(0.000)	(0.004)
Age 30 to 34	0.149***	0.004***	0.001***	0.146***
	(0.005)	(0.000)	(0.000)	(0.005)
Age 35 to 39	0.171***	0.004***	0.001***	0.167***
	(0.011)	(0.000)	(0.000)	(0.011)
Age older than 40	0.162***	0.004***	0.001***	0.159***
	(0.006)	(0.000)	(0.000)	(0.006)
Youngest child less than 6 years	Ref.			
Youngest child 6 to 12	-0.007	0.001*	0.001**	-0.007
	(0.008)	(0.000)	(0.000)	(0.007)
Youngest child 13 to 17	0.004	0.001	0.000	0.004
	(0.007)	(0.000)	(0.000)	(0.007)
Youngest child older than 18	-0.065***	0.000*	0.001***	-0.064***
	(0.006)	(0.000)	(0.000)	(0.006)
British Columbia	Ref.			
Newfoundland	-0.131***	-0.003***	-0.002***	-0.130***
	(0.003)	(0.000)	(0.000)	(0.003)
Prince Edward Island	-0.190***	-0.003***	-0.001***	-0.188***
	(0.001)	(0.000)	(0.000)	(0.001)

Nova Scotia	-0.176***	-0.001***	-0.001***	-0.176***
	(0.001)	(0.000)	(0.000)	(0.001)
New Brunswick	-0.180***	-0.002***	-0.001***	-0.180***
	(0.002)	(0.000)	(0.000)	(0.002)
Quebec	-0.071***	0.001***	0.000***	-0.070***
	(0.002)	(0.000)	(0.000)	(0.002)
Ontario	-0.036***	0.001***	0.000**	-0.036***
	(0.001)	(0.000)	(0.000)	(0.001)
Manitoba	-0.152***	-0.000***	-0.001***	-0.152***
	(0.002)	(0.000)	(0.000)	(0.002)
Saskatchewan	-0.099***	0.000	-0.000***	-0.100***
	(0.002)	(0.000)	(0.000)	(0.002)
Alberta	0.005**	0.001***	0.000	0.004*
	(0.002)	(0.000)	(0.000)	(0.002)
Nonunion	Ref.			
Union	-0.003	-0.003***	-0.003***	-0.003
	(0.007)	(0.000)	(0.000)	(0.006)
Temp	Ref.			
Permanent	0.079***	-0.002***	-0.001*	0.080***
	(0.012)	(0.000)	(0.000)	(0.011)
Multiple Jobs	Ref.			
Single Job	0.056***	0.000	0.000	0.056***
	(0.010)	(0.000)	(0.000)	(0.009)
Private Employee	Ref.			
Public Employee	0.140***	-0.002***	-0.005***	0.133***
	(0.013)	(0.000)	(0.000)	(0.015)
Tenure	0.012***	0.000	0.000	0.012***
	(0.001)	(0.000)	(0.000)	(0.001)
First Quarter	-0.018***	0.017***	0.013***	-0.019***
	(0.002)	(0.001)	(0.001)	(0.002)
Second Quarter	-0.028***	0.014***	0.009***	-0.029***

	(0.003)	(0.001)	(0.001)	(0.003)
Third Quarter	-0.020***	0.030***	0.025***	-0.018***
	(0.003)	(0.002)	(0.002)	(0.003)
Constant	2.601***	0.030***	-0.012***	2.550***
	(0.028)	(0.004)	(0.003)	(0.037)
F-statistics(remotepercent)				190142
F-statistics (remotesqr)				121252
Tests of endogeneity				32.8204***
Partial R-sq.				0.788
Observations	694,259	694,259	694,259	694,259
R-squared	0.362	0.788	0.790	0.362

Note(s): Significance at:***p<0.01;**p<0.05;*p<0.1. ‘Ref.’ indicates the reference group, which represents the baseline category in the regression table. Weighted regression models. Standard errors in parentheses are clustered at industry level. Controls include individual characteristics and additional job characteristics.

Source(s): Authors’ own work

Table 3A: Heterogeneity estimation results

	(1)	(2)	(3)	(4)	(5)
	Agriculture, forestry, fishing and hunting	Mining, quarrying, and oil and gas extraction	Construction	Manufacturing	Wholesale trade
VARIABLES	Lnwage	Lnwage	lnwage	Lnwage	lnwage
remotepercent	-1.494	0.209	-2.081	1.334***	13.351
	(2.792)	(0.854)	(1.600)	(0.389)	(7.636)
Remotesqr	7.309	-0.217	7.040	-3.186**	-28.699
	(13.076)	(1.747)	(4.326)	(1.107)	(16.259)

Table 3B: Heterogeneity estimation results

	(1)	(2)	(3)	(4)	(5)
	Retail trade	Transportation and warehousing	Information and cultural industries	Finance and insurance	Real estate and rental and leasing
VARIABLES	Lnwage	lnwage	lnwage	lnwage	Lnwage
remotepercent	-0.846	3.322	-3.880	-6.274	-13.461**
	(0.539)	(2.350)	(3.348)	(5.809)	(5.179)
remotesqr	2.393	-6.028	3.861	8.272	16.544**
	(1.672)	(3.984)	(3.459)	(8.047)	(6.421)

Table 3C Heterogeneity estimation results

	(1)	(2)	(3)	(4)	(5)
	Professional, scientific and technical services	Admin & support, waste mgnt and remediation services	Health care and social assistance	Accommodatio n and food services	Other services (except public admin)
VARIABLES	Lnwage	Lnwage	lnwage	lnwage	Lnwage
remotepercent	-0.094	14.633***	18.315***	1.376	-3.233
	(1.384)	(1.891)	(3.582)	(1.356)	(2.296)
remotesqr	0.032	-33.298***	-41.566***	-6.266	6.226
	(1.337)	(4.298)	(8.127)	(6.875)	(4.325)

Note(s): Significance at:***p<0.01;**p<0.05;*p<0.1
Weighted regression models. Standard errors in parentheses are clustered at industry level. Controls include individual characteristics and additional job characteristics
Source(s): Authors' own work

Table 4 Heterogeneity estimation results

VARIABLES	(1) Lnwage
Remotepercent	3.143***
	(0.133)
Remotesqr	-6.466***
	(0.200)
Digital	1.402***
	(0.099)
remote_digital	-7.494***
	(0.411)
remote2_digital	11.578***
	(0.291)
Constant	2.343***
	(0.033)
Observations	694,259
R-squared	0.369

Note(s): Significance at:***p<0.01;**p<0.05;*p<0.1
Weighted regression models. Standard errors in parentheses are clustered at industry level. Controls include individual characteristics and additional job characteristics
Source(s): Authors' own work

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