The current issue and full text archive of this journal is available on Emerald Insight at:
https://www.emerald.com/insight/0144-3585.htm

Work from home and labor market outcomes in developing economies

Nikita Céspedes-Reynaga
Department of Economics, San Ignacio de Loyola University, Lima, Peru and Department of Research, Central Reserve Bank of Peru, Lima, Peru

Received 8 August 2024
Revised 9 January 2025
27 February 2025
5 March 2025
Accepted 5 March 2025

Abstract

Purpose – This study aims to examine the theoretical and empirical effects of work from home (WFH) on labor market outcomes, including hours worked, consumption and income.

Design/methodology/approach – A formal model is introduced to explain the effects of WFH on consumption and hours worked. The model predicts that transitioning from office work (OW) to WFH increases both working hours and consumption. These predictions are tested using a difference-in-differences approach.

Findings – Empirical evidence from Peru supports the theoretical model's predictions: workers who transition from OW to WFH work an additional 2.3 h per week, see an 8.6% increase in income from their primary job and experience a reduction in per capita consumption. The effects on consumption align with the model's predictions after controlling for pandemic restrictions. Consumption declines are most pronounced in lower-income groups, where pandemic restrictions were stricter, while higher-income quintiles – less affected by these restrictions – show stable or increased consumption, suggesting that WFH facilitates consumption smoothing. Additionally, WFH's impact varies by gender, highlighting potential disparities in labor market outcomes.

Research limitations/implications – This study relies on a static model to assess WFH's impact, and the main analysis covers 2019–2020, later extended to four periods for robustness.

Practical implications – The WFH's positive effects on hours, consumption and income contribute to both academic discourse and policy development. From a policy perspective, the results suggest that supporting WFH aligns with efforts to improve consumption and well-being. If WFH remains widespread post-pandemic, labor regulations must adapt to balance its benefits, costs and responsibilities for both employers and employees.

Originality/value – We extend the labor market model to analyze the theoretical effects of WFH on hours worked, consumption and welfare. This is the first study to examine the empirical effect of WFH in developing economies like Peru.

Keywords Work from home, Teleworking, Remote work, Income, Hours, Consumption, Double-difference

Paper type Research paper

1. Introduction

Work from home (WFH) [1] has become a transformative force in global labor markets. While formally introduced in the 1970s, WFH expanded rapidly during the COVID-19 pandemic, reaching 42% of U.S. workers in 2020 (Bloom, 2020) and stabilizing at 33,8% by 2022 (BLS) [2]. In Peru, where data is available for 2021, approximately 9.5% of dependent workers were employed remotely. WFH differs significantly from Office Work (OW), particularly in time and resource savings due to commuting, which are more pronounced in developing economies due to inefficient transportation systems. In the United States, the average commuting time is approximately 54 min (U.S. Census Bureau, 2023). In the Latin America and Caribbean (LAC) region, the average weekday commuting time on public transportation is 77 min (Serebrisky *et al.*, 2019). This exceeds the average of 64 min for advanced economies, despite shorter average trip distances in the LAC region.

JEL Classification — J22, J31, J46, E21.

We would like to thank the participants of the V*iernes Económico seminar* at the Pontifical Catholic University of Peru for valuable comments. Additionally, we thanks Juan Manuel Garcia and Miguel Jaramillo for their feedback on a previous version of this document. We thank Patricia Mendoza for her help in editing this document. The opinions expressed herein are solely those of the authors and do not necessarily reflect the views of the Central Reserve Bank of Peru. Nikita Céspedes is a researcher at the BCRP and a member of the *Centro de Investigaciones Económicas y Políticas Sectoriales y Sociales* at USIL.

Journal of Economic Studies
Vol. 53 No. 2, 2026
pp. 378-400

e-ISSN: 1758-7387
p-ISSN: 0144-3585
DOI 10.1108/JES-08-2024-0528

Despite its rising prevalence, WFH remains underexplored in both theoretical and empirical research. This study seeks to fill this gap by presenting a theoretical model to assess the impact of WFH on labor market outcomes such as work hours, leisure, and consumption, and by testing the model's predictions using empirical microdata.

Studies on WFH, particularly in the context of the COVID-19 pandemic, have primarily focused on the profile of WFH workers and its features (Bloom, 2020). While previous studies (e.g. Bloom, 2020; Awada *et al.*, 2021; Barrero *et al.*, 2020) suggest WFH increases work hours, few formal models explicitly incorporate WFH's unique cost and time savings [3], these elements are crucial constraints households face when making consumption decisions. This study extends the neoclassical consumption-leisure model, predicting that WFH increases both working hours and consumption. However, this prediction is constrained by the model's static framework, which excludes savings and dynamic factors, necessitating empirical validation.

Peru presents an interesting case for empirical testing of WFH effects. Peru is chosen for its available information and the economic context that led to a massive increase in WFH. Peru's stringent confinement measures mandated WFH where feasible, making the switch to WFH an almost compulsory adaptation rather than a choice. This means that the extensive margin of WFH was not part of the worker's choice and can rather be seen as an exogenous shock. Also, the saving of time and resources when switching from OW to WFH is particularly high in Peru by considering its transportation system. In Lima Metropolitan the average commuting time was 87 min according to the 2010 Time Use Survey. Recent surveys suggest this has increased significantly, with commuting times in 2020 ranging from 30 to 180 min. Additionally, commuting costs can account for about 21% of the daily minimum wage [4].

Using 2019–2020 panel data, we apply a difference-in-differences (DD) model to estimate WFH's effects on income, work hours, and consumption. The treatment group consists of dependent workers in 2019 who switched to WFH in 2020, while the control group comprises those who remained in OW. The pandemic-triggered switch to WFH serves as an exogenous shock, justifying the methodology. In a non-pandemic context, i.e. after 2020, WFH would be part of workers' job choices, making necessary other identification strategy in order to measure the effects of WFH.

The findings show an increase in income and work hours due to WFH. However, contrary to theoretical predictions, remote workers' consumption decreased, mostly due to pandemic-imposed mobility restrictions limiting household (mainly low-income households) spending on certain items. Nevertheless, the data indicates that households with members in WFH were able to smooth their consumption in line with the weak permanent income hypothesis. Also, WFH seems to have heterogeneous effects by gender. It affects more man's income and women's hours of work.

The discrepancy between theoretical predictions and empirical findings on consumption likely arises from the model's static nature and the pandemic's unique conditions. Despite this, WFH proved to be an effective employment strategy, supporting income stability and consumption smoothing during economic uncertainty.

1.1 Scope of the study and regional relevance

WFH has become a key feature of the global labor market, driven by technological advancements even before COVID-19. Analyzing its impact on developing economies offers valuable policy insights. While this paper focuses on Peru, its theoretical framework applies broadly, as Peru shares key labor market characteristics with other Latin American (LA) economies. Given the limited research on WFH in developing economies—especially in LA—this study helps fill that gap. Online Appendix outlines Peru's macroeconomic and institutional context, highlighting its similarities with other LA economies.

2. Literature review

Research on WFH remains limited at the international level, with no published studies focusing specifically on Peru. Existing literature examines WFH's labor market implications, business organization, and its effects on worker well-being, health, and productivity.

ILO (2021) analyzes WFH in six Latin American (LA) countries during the COVID-19 pandemic, emphasizing its role in maintaining economic activity despite technological barriers. ILO (2020) estimates that 17% of jobs globally and 25% in developed economies can be performed remotely, highlighting the need for infrastructure investment to expand WFH opportunities.

Barrero *et al.* (2020) surveyed U.S. workers during the pandemic (May–August 2020) and found 54 min of daily time savings, with 35% allocated to additional work hours. Similarly, Awada *et al.* (2021) reported a 1.5-h increase in workstation time per WFH day. Hansen *et al.* (2023) analyzed 250 million online job postings across five English-speaking countries, confirming that the pandemic significantly accelerated WFH adoption.

WFH was studied before the pandemic, particularly through experimental settings. Bloom *et al.* (2015) conducted a randomized natural experiment at a NASDAQ-listed Chinese company, assigning employees to home or office work for nine months. Key findings included: (1) 13% performance improvement among WFH employees. (2) Higher job satisfaction and lower attrition rates (50% decline). (3) No negative spillover effects on in-office workers.

A major benefit of WFH is the elimination of commuting costs, which play a crucial role in job and household decisions. The literature on the importance of commuting costs in household work decisions is extensive and forms part of a larger body of work on urban economics (Eliasson *et al.*, 2020; Heblich *et al.*, 2020; Delventhal *et al.*, 2022). Long commutes are linked to: (1) Lower well-being, stress, and fatigue (Stone and Schneider, 2016). (2) Reduced family time and lower quality interactions with children (Gimenez-Nadal and Molina, 2016). (3) Physical and psychological health issues, including higher blood pressure, anxiety, and fatigue (Kahneman *et al.*, 2004; Koslowsky *et al.*, 1995; Stutzer and Frey, 2008). (4) Low perceived utility of commuting, often classified as disutility (Kahneman *et al.*, 2004; Kahneman and Krueger, 2006).

Despite WFH's global rise, no studies have integrated it into neoclassical labor market models. This study addresses that gap by extending the traditional labor supply model to incorporate WFH's key characteristics. It is also the first study of WFH in developing economies such as Peru.

3. A theoretical model of the labor market with WFH

We present a theoretical model that extends the static neoclassical labor supply model (also known as the consumption-leisure model) to analyze the impact of WFH on the labor market. In this framework, workers make decisions regarding work hours, leisure, and consumption while accounting for two key aspects of remote work: commuting time and costs. These factors are particularly significant in developing economies.

In the OW model, total available time is standardized to 1, with hours allocated to: work (L), leisure (L^s), and commuting (L^*). Since commuting is mandatory in OW, workers cannot independently choose L^*. When transitioning to *WFH* $(\mathrm{L}^* = 0)$, total available time for work and leisure increases, requiring workers to decide time reallocation.

$$L^s + L + L^* = 1$$

In OW, commuting incurs a fixed cost, proportional to commuting time $(\eta = \eta(L^*), \eta' > 0)$ (longer commutes increase costs). This cost is related to transportation expenses and is assumed to be a fixed cost in the consumption decision. In other words, once a worker takes an OW job, they also accept the associated commuting costs. This assumption allows us to separate commuting costs from other consumption items (c) in the budget constraint. The worker's optimization problem in OW is:

$$Max_{c,L,L^s} U(c, L^s)$$

Subject to:

$$c + \eta = wL$$

$$L^s + L + L^* = 1.$$

where **w** is the hourly wage. In this specification, we consider that the consumption-leisure decision problem of a WFH worker occurs when $L^* = 0$ and $\eta = 0$. Notice that the two features of WFH are reflected in the financial budget constraint as well as in the time constraint. To explain the effect of WFH on hours worked, it is necessary to solve the problem; the optimal solution is represented by the equation that relates the marginal rate of substitution of consumption-leisure and the salary: $\left[w = -\frac{U_L}{U_c}\right]$. For further analytical insights, we introduce the following utility function:

$$U(C, 1 - L - L^*) = \frac{C^{1-\sigma}}{1-\sigma} + \theta \frac{(L + L^*)^{1+1/\psi}}{1 + 1/\psi}; \ \theta < 0.$$

When $L^* = 0$, the utility function is among the most used in macroeconomics. Also, σ and ψ represent the risk aversion and the Frisch elasticity, respectively. Notice that in this utility function, commuting hours have a negative and direct effect on welfare, which is consistent with the empirical evidence provided by the literature (Van Ommeren and Fosgerau, 2009). However, this formulation may also capture the indirect effects of commuting on welfare that act through hours of work and consumption.

The solution to the worker optimization problem is summarized in terms of the consumption-leisure Marginal Rate of Substitution (MRS):

$$MRS = -\frac{U_L}{U_c} = \frac{(-\theta)\,(L + L^*)^{(1/\psi)}}{(wL - \eta)^{-\sigma}}$$

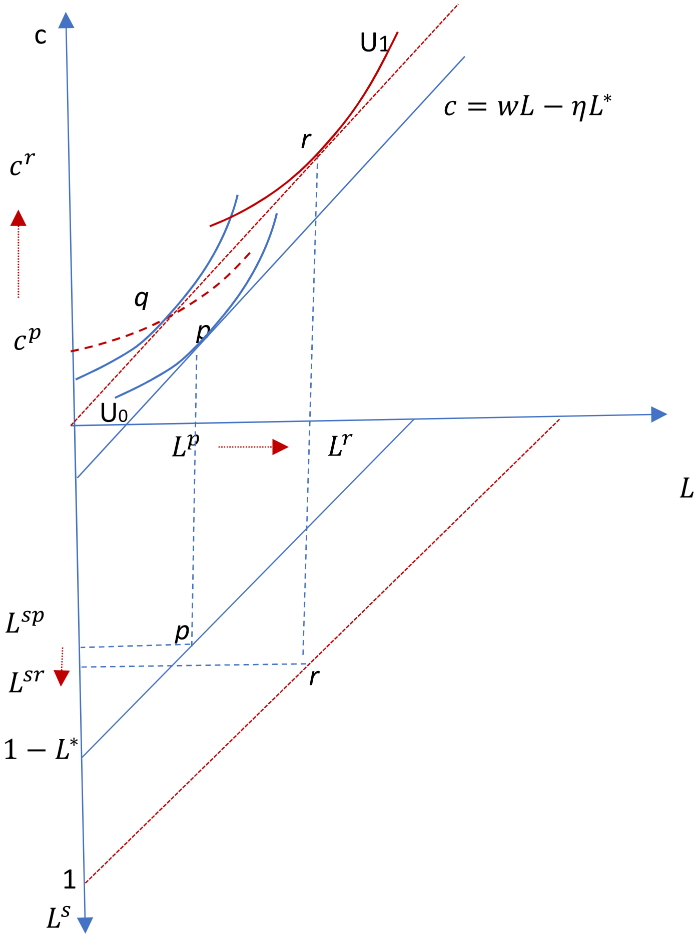
$$MRS = \left[(-\theta)\,(L + L^*)^{(1/\psi)}\right] * \left[\frac{1}{(wL - \eta)^{-\sigma}}\right]$$

This equation captures two features of WFH that affect consumption and hours of work in equilibrium. The first term, $(-\theta)(L + L^*)^{\left(\frac{1}{\psi}\right)} > 0$, depends positively on L^* and represents the effect of longer available hours. The second term, $\frac{1}{(wL-\eta)^{-\sigma}} > 0$, depends negatively on η and captures the effect of the commuting cost reduction due to WFH. From Figure 1, the OW equilibrium is at point "*p*" when the salary is equal to the MRS between consumption and leisure. According to the previous equation, there are two mechanisms with opposite effects on hours that are discussed separately. Although these mechanisms are presented simultaneously, for illustrative purposes, we first discuss the effect of greater resources on the budget constraint and then discuss the effect of fewer commuting hours on the time constraint.

3.1 Effect of lower commuting costs ($\eta = 0$)

WFH eliminates commuting costs, increasing workers' available income. This additional income, independent of wages, influences consumption through the income effect. In the figure, this is shown by a parallel leftward shift of the financial budget constraint, moving equilibrium from point *p* to r. Since both consumption and leisure are assumed to be normal goods, workers can allocate commuting savings toward both goods.

In this scenario, increased leisure does not necessarily reduce working hours, as workers gain extra time from eliminating commutes. A reduction in work hours occurs only if the additional leisure demand exceeds the time freed up by WFH. Thus, the income effect's impact



Note(s): The top of the figure illustrates equilibrium in terms of consumption and work hours, while the bottom depicts leisure determination. Initially, equilibrium is at point *p* (OW). With WFH, time and resource constraints change, leading to a new equilibrium at point *r*. The first shift occurs due to higher income (from reduced commuting costs), which raises the budget constraint, moving equilibrium to point *q* — where consumption increases and work decreases — reflecting the income effect. Additionally, a change in the marginal rate of substitution (MRS) shifts the indifference curve, further adjusting equilibrium to point *r*, where the budget constraint reaches the highest indifference curve. The second shift stems from greater time availability with WFH, as shown in the bottom part of the figure, where leisure increases from point *p* to point *r*
Source(s): Author's own creation

Figure 1. Determination of consumption, hours of work and leisure in WFH and OW

on reducing work hours is weaker when workers already have more available time (i.e. when ($L^* > 0$).

3.2 Effect of increased time on MRS

WFH increases available time for both work and leisure, lowering the marginal utility of leisure in the initial equilibrium. As a result, the marginal rate of substitution (MRS) falls below the wage, shifting the indifference curve map from U_0 to U_1. At point *p*, after accounting for the income effect, remote workers require more consumption per unit of additional leisure to maintain utility. To reach a new equilibrium, they must work more to raise the marginal utility of leisure, thereby increasing the MRS.

These two mechanisms have opposite effects on work hours. However, for median income levels, the income effect is relatively small and is likely outweighed by the additional available hours. Consequently, WFH is expected to increase both working hours and consumption. In Figure 1, equilibrium would fall between points *q* and *r*, with the final position closer to *r*.

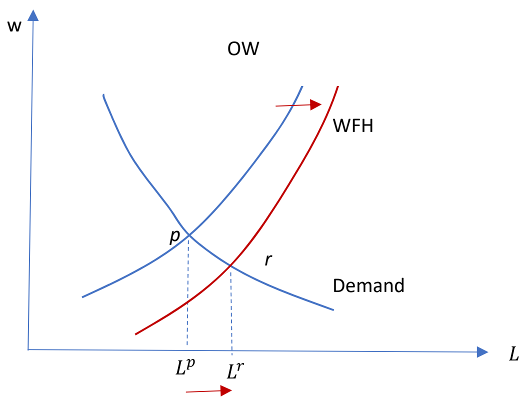
A key result of the WFH model is the potential positive correlation between leisure and employment. In the standard neoclassical labor model for OW, leisure and work hours have a strict negative relationship—more leisure necessarily reduces work hours. However, in the WFH model, freed-up time allows for an increase in both leisure and work, suggesting a possible positive correlation between them. This aspect remains underexplored in the theoretical literature.

3.2.1 The welfare effects of WFH. The model predicts that WFH improves worker well-being by increasing both consumption and leisure. Unlike in OW, where more work reduces leisure, WFH relaxes time constraints, allowing both to increase simultaneously. Graphically, this is reflected in higher utility at point *r* (WFH) compared to point *p* (OW), as indifference curves shift with changes in the marginal rate of substitution (MRS).

The effect of WFH on hours worked can be illustrated using labor supply and demand. In Figure 2, the WFH labor supply curve shifts rightward compared to OW, assuming WFH increases work hours. If labor demand remains unchanged, equilibrium moves from point *p* (OW) to point *r* (WFH), where $L^r > L^p$, indicating longer hours for remote workers.

Work hours may rise even further if WFH boosts productivity, shifting labor demand upward. Research suggests that productivity gains are more pronounced when WFH is optional (Awada *et al.*, 2021; Barrero *et al.*, 2021; Guler *et al.*, 2021). Additionally, since the WFH labor supply curve is flatter than OW's, a positive productivity shock increases hours worked more in WFH settings.

While this model offers a static view of WFH's effects, a dynamic general equilibrium approach is needed to capture broader impacts on consumption and savings. Given WFH's growing role post-pandemic, studying it within a general equilibrium framework is warranted.



Source(s): Author's own creation

Figure 2. The labor market equilibrium of WFH and OW

Overall, the model suggests that WFH increases both work hours and consumption. While the impact on consumption is clear, the effect on work hours is theoretically ambiguous due to opposing forces. Therefore, its final impact must be determined empirically.

4. Stylized facts about WFH in Peru

Peru introduced remote work and teleworking in 2013 with the Remote Work Law (Law 30,036). Initially, adoption was minimal, with only 3,000 workers nationwide by 2019 (Figure 3). However, WFH expanded significantly in 2020 due to the COVID-19 pandemic, prompting regulatory revisions in March 2020 to promote its use. In 2023, post-pandemic adjustments further refined regulations to align with regular labor conditions.

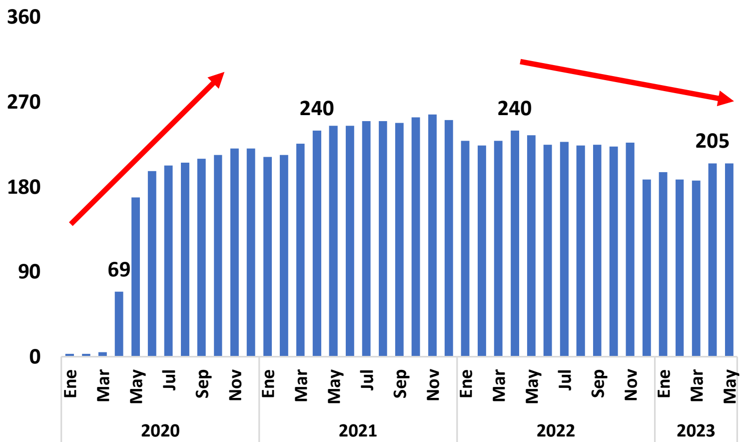
The Ministry of Labor (MTPE) tracks WFH through Electronic Payroll. In 2019, only 3,000 formal WFH jobs existed, but numbers surged during the pandemic, peaking at 257,000 in October 2021. By 2023, WFH stabilized at around 200,000 jobs, with 89% concentrated in the service sector. Figure 3 illustrates this trend, showing a sharp rise during the pandemic and sustained levels afterward. The continued prevalence of WFH three years after the pandemic suggests that its advantages may outweigh its drawbacks over time.

4.1 Characteristics of remote work and/or teleworking according to EHANO

The National Household Survey (ENAHO) provides a comprehensive overview of WFH in Peru, covering all dependent workers. In 2021, ENAHO recorded 773,000 remote workers, representing 9.5% of dependent workers. While ENAHO data are broader than the Electronic Payroll, both sources yield similar estimates under comparable criteria. For instance, ENAHO reported 260,000 formal private-sector remote workers exceeding 20 h per week in 2021, while the Electronic Payroll recorded an annual average of 241,000.

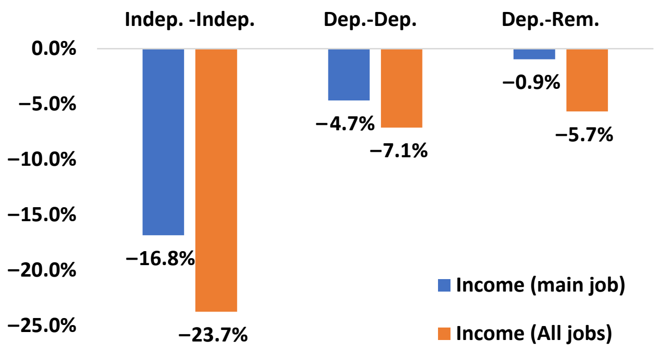
ENAHO also offers insights into WFH characteristics for 2020–2021 (Table 11 in online Appendix).

(1) Gender: Women hold 57% of remote jobs, with 16.3% of female employees working remotely, compared to 6.6% of men.



Source(s): Author's own creation from MTPE-Electronic Payroll

Figure 3. Teleworking and remote work positions in the private sector (in thousands)



Note(s): Workers who remained in the same category either as dependent workers (Dep. – Dep.) or as independent workers (Indep. – Indep.) between 2019 and 2020 are considered. The Dep.-Rem. case corresponds to workers who went from being OW dependents in 2019 to WFH dependents in 2020
Source(s): Author's own creation from ENAHO 2019-2020 panel sample

Figure 4. Percentage change in real income from main job between 2019 and 2020 (panel sample)

(2) Economic Sector: The service sector dominates WFH, employing 88% of remote workers, with 18.4% of its workforce engaged in remote jobs. Trade and manufacturing follow, accounting for 10.1% combined.

(3) Occupation Type: WFH is concentrated among white-collar workers (98%), while blue-collar roles remain largely in-person due to job requirements.

(4) Geographic Region: Remote workers are primarily in urban areas, particularly metropolitan Lima, where service jobs, large companies, and strong telecommunications infrastructure facilitate WFH.

(5) Sector and Company Size: 77% of remote jobs are formal, and 59% are in large companies (500+ employees).

These findings highlight WFH's growing role in Peru's labor market, especially in the formal service sector and large enterprises, while also underscoring the challenges of broader implementation.

4.2 The effect of WFH on income and hours worked

WFH played a crucial role in mitigating the COVID-19 pandemic's impact on Peru's labor market, helping preserve formal employment. In 2020, 9.9% of dependent workers engaged in WFH, primarily in highly productive formal positions, leading to significantly higher incomes. These income differences are consistent across job categories, whether analyzed by demand factors (e.g. company size, sector) or supply factors (e.g., gender, age) (see Table 1).

However, average data alone do not establish causality. Income effects may result from productivity gains due to increased worker effort or reduced income loss for remote workers during the pandemic. To assess WFH's impact on income and hours worked, we use ENAHO 2019–2020 panel data and apply a double difference estimator (see Table 1 and 10, online Appendix).

Table 1 (also Figure 4) compares income changes between 2019 and 2020 for WFH workers (treatment group) and those who remained in OW (control group). The double difference estimator shows that WFH increased income by 3.7% in 2020. While WFH workers saw a 0.9% income decline, on-site workers experienced a larger drop (−4.7%), indicating a

Table 1. Income and hours worked in the main job according to panel sample (S/. of 2022)

	Situation at *t*	Situation at *t*+1	Panel 2019–2020 2019 *t*	2020 *t*+1	% change	*p*-value (*t*-test)
Income						
	Independent	Independent	779	648	−16.8%	0.000***
		Dependent	834	981	17.7%	0.000***
		Remote	591	2,488	320.7%	0.000***
	Dependent	Independent	1,077	560	−48.0%	0.000***
		Dependent	1,453	1,386	−4.7%	0.123
		Remote	2,156	2,135	−0.9%	0.006***
Hours of work(week)						
	Independent	Independent	34.1	31.4	−8.1%	0.001***
		Dependent	28.3	34.2	20.7%	0.000***
		Remote	18.2	38.6	112.0%	0.212
	Dependent	Independent	37.2	25.1	−32.5%	0.000***
		Dependent	41.0	39.9	−2.8%	0.012**
		Remote	34.9	35.3	1.0%	0.592
Income per hour						
	Independent	Independent	5.3	4.8	−9.9%	0.000***
		Dependent	6.9	6.7	−3.1%	0.394
		Remote	7.5	15.0	98.4%	0.012**
	Dependent	Independent	6.7	5.2	−23.0%	0.000
		Dependent	8.2	8.1	−2.0%	0.508
		Remote	14.4	14.1	−2.2%	0.104

Note(s): Total income from main work is considered. The dependent category includes employees, laborers, and household workers, while the independent category comprises employers, unpaid family workers, and self-employed individuals. The "remote" category refers to dependent workers engaged in remote work and/or telework. We report the *p*-value of the *t*-test comparing 2020 and 2019 means for each category, where ***indicates a highly significant difference in means
Source(s): Author's own creation from ENAHO 2019–2020

stronger negative impact on those unable to transition to WFH. An alternative comparison with independent workers as control group, whose income fell by 17%, further supports the hypothesis that WFH helped stabilize earnings. A similar double difference calculation for hours worked and hourly wages shows that WFH increased hours worked by 4.3% but slightly reduced hourly income by 1.1% between 2019 and 2020.

5. The empirical model

While previous analyses suggest a relationship between WFH, income, and hours worked, average data alone are not conclusive. To rigorously assess statistical significance and control for other variables, we use a panel regression model with fixed effects, specified as follows:

$$Ln(y_{it}) = \alpha + \alpha_i + \delta_t + \sum_{r\neq 2019} T_i \times 1[\mathrm{t} = r]\beta_r + \theta z_{it} + \varepsilon_{it}, \tag{1}$$

where, T_i denotes the worker job modality in period t, δ_t is the annual fixed effect and α_i is the individual fix effect. Y_{it} represents the outcome, which can be income, hours or consumption. The variable Z_{it} represents a set of controls designed to address job heterogeneity and enhance comparability between treatment and control groups. These controls include fixed effects (Table 2) that account for variations across both the supply and demand sides of the labor market, effectively serving as a matching mechanism between treated and control groups.

Table 2. Description of fixed effects

Fixed effects	Description
Individual fixed effects	Capture worker-specific heterogeneity by considering skills, abilities, and other personal attributes
Gender, age	Control for gender-related factors and life-cycle events
Year fixed effects, economic sector	Account for broader economic conditions
Employment type, multiple jobholding	Control for job type and employment structure
Informality, income quintile	Adjust for income level and employment informality

Source(s): Author's own creation

Individual-level fixed effects (e.g., gender, age) account for skills, abilities, and life-cycle factors affecting employment outcomes. Job-level fixed effects (e.g., occupation, employment type) control for firm-level dynamics. Labor market fixed effects (e.g., sector, multiple jobholding, informality, income quintile) address broader heterogeneity. These controls create a robust framework for analyzing WFH's impact while minimizing biases from worker and job variations.

The parameter β_r represents the difference-in-difference (DD) estimator, capturing WFH's effect on workers' outcomes. Fixed-effects regression controls for observable time-invariant variables (e.g., gender) and unobservable constant factors (e.g., innate ability). Since WFH was exogenously imposed in 2020 by government regulations, concerns about endogeneity are reduced [5]. Workers did not self-select into WFH; instead, the shift occurred externally to mitigate COVID-19, allowing us to analyze adjustments at the intensive margin (wages, hours, consumption).

6. Results

6.1 Effects of WFH on workers income and hours of work

The impact of WFH on income and hours worked is assessed using ENAHO 2019–2020 panel data, a nationally representative sample of 3,587 dependent workers. The analysis focuses on this period, as WFH was exogenously imposed during the pandemic. From 2021 onward, as WFH became more common and voluntary, a different methodology would be required. The study is also limited by ENAHO's telework data availability (2020–2021 only).

The model estimates income and hourly income (logarithms) and weekly hours worked (levels) for both the primary job and total employment. Control variables include age, occupation, informality, and multiple jobs.

Results are presented in Table 3, and we stress the following findings: (1) WFH led to an 8.6% increase in income, meaning remote workers saw smaller income losses than in-person workers. (2) Remote workers worked 2,3 additional hours per week, a significant effect consistent across all job categories. This positive effect on hours worked aligns with findings by Awada *et al*. (2021), Bloom *et al*. (2015), and Barrero *et al*. (2020). (3) While WFH resulted in a 5% increase in hourly income, this effect was not statistically significant, suggesting longer hours offset wage gains.

WFH allowed workers to mitigate the income effects of the COVID-19 pandemic. In 2020, the labor market saw a significant contraction, with a 21% reduction in per capita income and a 13% drop in employment. The reduction was smaller among formal and dependent workers. For the panel sample, controlling for labor market entry and exit, income decreased by approximately 3.9% (see Table 1), while the reduction was smaller for dependent workers who switched to WFH (1%). Using self-employed workers as a control group, who experienced a 24% drop in main income and a 17% drop in main job income, suggests that the income smoothing effect of WFH could be even more pronounced. Therefore, WFH emerges as an

Table 3. Double difference estimator measuring effects of WFH on labor income and working hours

	Main job Income (1)	Hours (2)	Income/Hour (3)	All jobs Income (4)	Hours (5)	Income/Hour (6)
All sample						
Diff-Diff estimator of WFH	0.086**	2.320**	0.051	0.067*	2.227**	0.024
	(0.03)	(0.81)	(0.03)	(0.03)	(0.85)	(0.03)
No. of obs	6,900	6,900	6,900	6,900	6,900	6,900
R-squared	0.836	0.721	0.8	0.834	0.71	0.801
Estimation by informality						
Formal	0.079**	2.859***	0.028	0.061*	2.838**	0.008
	(0.02)	(0.83)	(0.03)	(0.02)	(0.92)	(0.04)
Informal	−0.192	−2,117	−0.074	−0.260*	−3,776	−0.134
	(0.13)	(3.08)	(0.11)	(0.13)	(3.17)	(0.12)

Note(s): The model considers income and hourly income in logarithms, while hours worked per week are expressed in hours. In the estimation by informality/formality, we divide the sample into formal and informal workers. *Statistically significant at 10%, ** Statistically significant at 5%, *** Statistically significant at 1%. Standard error in parentheses
Source(s): Author's own creation from EHANO panel sample 2019–2020

insurance mechanism that helped maintain income levels for dependent jobs during the significant negative shock experienced by the Peruvian labor market.

The findings reveal that WFH led to increases in both income and hours worked, with a significant positive impact on overall income. WFH emerged as a critical mechanism for income stabilization during the COVID-19 pandemic, playing a pivotal role in maintaining employment and income levels during a severe economic downturn. This analysis underscores the value of WFH as a sustainable employment strategy, particularly in times of economic uncertainty.

6.2 Effects of WFH on household consumption and household income

WFH played a crucial role in mitigating income shocks during the pandemic, but a broader assessment requires analyzing its impact on household per capita consumption. While households employed various strategies to manage economic uncertainty, WFH emerged as a key mechanism for stabilizing income among dependent workers and may serve as a buffer against future economic shocks.

Using sample averages of the panel data for 2019–2020, the pandemic led to a 15.7% decline in average consumption, with WFH households experiencing a sharper 23.4% drop (Table 10, online Appendix). To assess the statistical significance of WFH on consumption and per capita income, we use the Equation (1) to estimate the DD estimator, we find that WFH reduced per capita consumption by 6.5% among dependent workers (Table 4), confirming a causal effect. Also, WFH had no significant impact on household income, suggesting that households relied on additional smoothing strategies beyond WFH to offset income changes.

Additionally, the exercise is carried out considering the household per capita income as the dependent value. In this case, we found an insignificant effect of WFH on Household Income. It is recalled that in the previous section it was shown that WFH affects workers income to a small extent, however, the result of this section suggests that when we aggregate the effects of WFH on income at a household level the WFH effect could be reduced. The suggested explanation for this result is that households with dependent workers would have additional smoothing strategies in addition to WFH that would have.

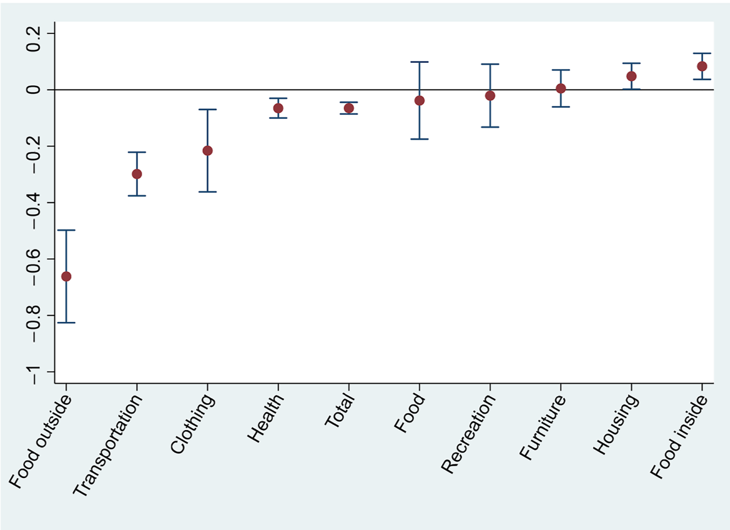
Table 4. Effects of WFH on per capita income, expenditure and savings (double difference estimator in panel model with fixed effects)

	Income (1)	Consumption (2)	Saving (3)
Diff-Diff estimator of WFH	0.040*	−0.065***	0.082***
	(0.02)	(0.01)	(0.02)
No. of obs	6,900	6,900	6,900
R-squared	0.909	0.966	0.653

Note(s): The model considers income and hourly income in logarithms. *Statistically significant at 10%, **Statistically significant at 5%, ***Statistically significant at 1%. Standard error in parentheses
Source(s): Author's own creation from EHANO panel sample 2019–2020

6.2.1 Differentiated effects on consumption categories. The negative effect of WFH on consumption contrasts with minimal changes in household income due to pandemic-related restrictions, which reduced spending on transportation, entertainment, healthcare, and dining out. Analyzing the impact of WFH across different consumption categories reveals that the negative effect of WFH on consumption is most noticeable in categories heavily impacted by restrictions, such as dining out, transportation, communications, clothing, and healthcare. In contrast, the effect is smaller and less significant in categories less affected by confinement, such as groceries, housing, and household goods (Figure 5). This suggests that WFH helped stabilize the consumption of essential items.

Research indicates that WFH may have negative effects on household expenditures. WFH shifts consumption patterns, reducing urban spending while increasing suburban expenses (Barrero *et al.*, 2021). Similar trends may affect local tax revenues and commercial activity, highlighting the need for further analysis in a dynamic general equilibrium framework to better



Source(s): Author's own creation from EHANO panel sample 2019 – 2020

Figure 5. Effect of WFH on per capita consumption by consumption groups (double difference estimator in panel model with fixed effects)

understand its distributional impacts and identify both beneficiaries and those adversely affected by the shift to remote work.

6.2.2 Consumption smoothing across income quintiles. To complement the analysis the DD estimator was calculated according to income quintiles for each consumption group. The results, presented in Figure 7 (online Appendix), indicate that the effect of WFH on consumption was positive, but not significant, in the higher-income quintiles across almost most consumption groups, while a negative effect was observed in the lower-income quintiles. This pattern holds even in consumption groups where restrictions were stringent and the drop in consumption was significant, such as transportation and dining out, with the double difference estimator being higher in the higher-income quintiles.

We hypothesize that households with members working remotely can smooth their income, as previously shown. However, they also experience a reduction in their expenses due to the pandemic circumstances, allowing them to cut certain costs. The reduction in spending in these consumption groups was smaller in the higher-income quintiles and in households with remote workers. This suggests that the pandemic led these households to decrease spending on activities they might have otherwise engaged in, such as entertainment, dining out, and transportation.

When combining income and expenditure effects, the negative consumption impact was significant, while income changes remained minor. This phenomenon can be explained by pandemic restrictions on certain consumption categories and the savings decisions made by workers whose consumption was restricted. Essentially, an additional mechanism is activated: the savings induced by the pandemic restrictions on dependent workers. The DD estimator finds that savings [6] increased by 8.2% due to WFH. This improvement in savings is evident across the entire savings distribution. Figure 6 shows that the distribution of the savings rate for dependent workers who switched to WFH in 2020 spans the entire range, while savings among face-to-face workers remain around the average of the savings distribution. The effect of WFH on savings is lower in high-income quintiles, supporting the hypothesis that WFH facilitated greater consumption smoothing among high-income workers.

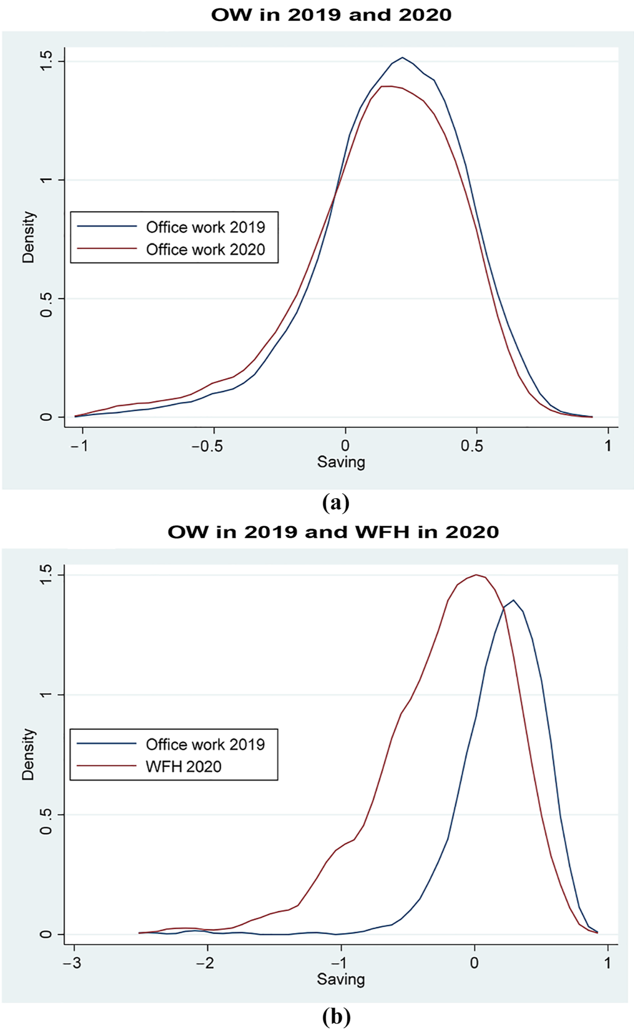
The model also reveals heterogeneous effects based on workers' informality status. As indicated by the stylized facts, WFH is more prevalent in high-productivity, high-income jobs, which are predominantly formal and concentrated in the upper income quintiles, typically within high-productivity sectors. Consequently, the estimated impact of WFH is more pronounced among formal workers compared to informal workers (see Table 2 for the formal/informal comparison) and is strongest in the highest income quintiles for consumption (Figure 7a).

Summarizing this section, WFH minimized income disruptions, but restrictions forced a shift in consumption patterns, leading to increased savings. In the highest income quintile, workers experienced less change in income, consumption, and savings, suggesting WFH helped smooth economic shocks and provided a stabilizing mechanism for household well-being during uncertainty (see Figure 8).

6.3 Sensitivity analysis of results to longer data panels

The initial findings are based on a two-period panel (2019–2020) with 3,587 dependent workers. To assess whether pre-2019 trends influence these results, we extend the analysis using three- and four-period panels (2017–2020). Although this approach reduces the sample size (1743 workers observed over three years), it provides a robustness check and tests the parallel trends assumption in the difference-in-differences methodology.

Results are provided in Table 5. Results remain consistent across different panel lengths: WFH increases hours worked and main income. It has no significant effect on hourly income and WFH reduces consumption but increases savings. Also, Parallel trends assumption holds: Figure 7 (online Appendix) confirms that trends for treated (WFH) and control (OW) groups were parallel before 2020, reinforcing the validity of the methodology (see Figure 9 for a



Note(s): Savings are defined as the difference between per capita income and expenditure, expressed as a percentage of per capita income
Source(s): Author's own creation

Figure 6. Distribution of savings in 2019 and 2020 for dependent workers

graphical illustration). A placebo test further supports parallel trends before 2020 (see Section 6.7). These results remain robust to changes in the observation period, confirming the stability and reliability of the findings.

6.3.1 The role of sample composition changes due to pandemic. The study relies on a panel of dependent workers; however, the pandemic has led to employment disruptions, including job losses and labor transitions, which may have affected the sample size and composition. Such changes could introduce attrition bias, potentially influencing the model's outcomes.

Table 5. Double difference estimator for the 9 indicators with 2018–2020 panel data

	Main job			All jobs					
	Income (1)	Hours (2)	Income/ Hours (3)	Income (4)	Hours (5)	Income/ Hours (6)	Income (7)	Consumption (8)	Saving (9)
2018–2020 panel data									
Diff-Diff estimator of WFH	0.089**	2.198*	0.049	0.058	2.182*	0.012	0.055*	−0.072***	0.095***
	(0.03)	(0.90)	(0.03)	(0.03)	(0.96)	(0.03)	(0.02)	(0.01)	(0.02)
No. Of obs	5,231	5,231	5,231	5,231	5,231	5,231	5,231	5,231	5,231
R-squared	0.782	0.627	0.743	0.784	0.611	0.739	0.889	0.951	0.569
2017–2020 panel data									
Diff-Diff estimator of WFH	0.106**	2.345*	0.057	0.058	2.680*	−0.021	0.059*	−0.074***	0.104***
	(0.04)	(1.13)	(0.04)	(0.04)	(1.24)	(0.04)	(0.03)	(0.02)	(0.02)
No. Of obs	3,307	3,268	3,268	3,307	3,307	3,307	3,307	3,307	3,307
R-squared	0.764	0.600	0.700	0.769	0.568	0.692	0.875	0.942	0.502

Note(s): The cut-off period is 2019, the data before the cut-off point correspond to 2018–2019, and the data after the cut-off to 2020. The 2018–2020 (2017–2020) panel sample corresponds to 1743 (826) dependent workers observed three (four) consecutive times. *Statistically significant at 10%, **Statistically significant at 5%, ***Statistically significant at 1%. Standard error in parentheses

Source(s): Author's own creation from EHANO panel sample 2017–2020, 2018–2020

To assess the impact of sample composition, we estimate the empirical model using panels of different lengths. Specifically, we compare the results obtained from a three-period and a four-period panel with those from the original two-period panel. The findings remain consistent across these specifications (see Table 5). Additionally, as discussed in Section 6.7, we perform a robustness analysis using bootstrapping with a smaller sample. The distribution of estimated parameters for each outcome indicates that the average effect closely aligns with the results from the full sample (see Table 9).

These robustness checks confirm that variations in sample composition do not significantly affect the estimated effects of WFH.

6.4 WFH and consumption smoothness

The analysis suggests that households with remote workers struggled to smooth consumption during the pandemic. While expenses dropped significantly, income remained stable, indicating a potential imbalance. To formally assess consumption smoothing, we estimate a consumption model linking consumption to permanent and transitory income, following Meng (2003) and Paxson (1992):

$$C_i = \alpha + \beta Y_i^P + \gamma Y_i^T + \mu UC_i + \lambda X_i + \varepsilon_i, \tag{2}$$

where C_i is the per capita consumption of household, Y_i^P is the permanent income, Y_i^T is the transitory income for household i, UC_i is the income uncertainty faced by household i, X_i is the vector of household characteristics, and ε_i the error term.

The weak permanent income hypothesis holds if $\beta > \gamma$, meaning consumption is primarily driven by permanent income, allowing households to smooth consumption despite income fluctuations.

Building on Céspedes and Talledo (2024), who found that Peruvian households smooth consumption despite economic shocks, we extend their approach to evaluate WFH's role in consumption smoothing. Due to panel data limitations, WFH records exist only for 2020–2021, requiring data from three prior periods (before 2019) to estimate permanent income. Consequently, the sample of households with remote workers is reduced.

Table 6 confirms that, on average, Peruvian households smoothed consumption between 2019 and 2021, with a higher marginal propensity to consume from permanent income (β) than from transitory income (γ). Specifically, households with remote workers successfully smoothed consumption between 2020 and 2021 (column 7). However, mixed results emerge when considering economic shocks: (1) Households with remote workers facing job loss or business bankruptcy struggled to smooth consumption and (2) Households without such shocks managed to smooth consumption between 2019 and 2021 (column 8). These findings suggest that while WFH supports consumption smoothing, severe economic shocks can disrupt this mechanism, even when one household member works remotely.

6.5 Robustness analysis

To assess the stability of our results, we applied the double difference estimator to nine indicators using data on dependent workers (2019–2020). While our pseudo-experimental approach does not follow strict randomization, we conducted a resampling exercise to test whether results vary across different samples.

The procedure involved randomly selecting a sample (60% of total) from the control group and comparing it with the treatment group computing the DD estimator for each indicator. Given the small size of the remote worker group, resampling was performed only within the treatment group. Figure 10 presents the distribution of the double difference estimators across 10,000 replications for the nine indicators. The findings show that the estimator's distribution centers around the values obtained with the full sample, confirming that the estimates are stable and robust.

Table 6. Consumption smoothing test (2009–2021)

	Sample: 2009–2021 Total workers			Sample: 2019–2021 Total workers			Sample: 2019–2021 Workers in WFH		
	All (1)	With economic shock (2)	Without economic shock (3)	All (4)	With economic shock (5)	Without economic shock (6)	All (7)	With economic shock (8)	Without economic shock (9)
Permanent income	0.502***	0.527***	0.500***	0.498***	0.448***	0.501***	0.601***	0.288***	0.609***
	(29.35)	(17.59)	(28.24)	(31.86)	(14.24)	(30.64)	(8.26)	(3.89)	(8.19)
Transitory income	0.161***	0.247***	0.156***	0.214***	0.288***	0.208***	0.231***	0.299**	0.216**
	(9.57)	(7.09)	(8.96)	(9.32)	(6.41)	(8.60)	(3.37)	(3.13)	(2.89)
No. obs	46,525	2,061	44,464	27,445	1,888	25,557	663	62	601
Prob → F	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
R-squared	0.69	0.69	0.69	0.675	0.596	0.68	0.704	0.817	0.704
test of consumption smoothness (prob → F)	0.000***	0.000***	0.000***	0.000***	0.044**	0.000***	0.008***	0.9237	0.007***

Note(s): The sample considers households that appear to be in three consecutive periods. *Statistically significant at 10%, **Statistically significant at 5%, ***Statistically significant at 1%. t-statistics in parentheses. Only economic shocks (job loss and family business bankruptcy) are considered
Source(s): Author's own creation from ENAHO 2007–2021

6.6 Effect of WFH by gender of workers

WFH is particularly appealing to women, as preference surveys suggest they favor remote work more than men [7]. In Peru, a higher proportion of women work remotely. However, research indicates that WFH may also exacerbate gender inequality [8], as women often face greater challenges in balancing work with household responsibilities, such as childcare.

The main benefit of WFH—time and cost savings—influences household decision-making, but its impact varies by gender and age. WFH blurs the boundaries between work and domestic tasks, which are often gendered (EIGE, 2021; Eurofound, 2022; ILO, 2021). Women, who typically take on more household duties, may experience greater disruptions to their workday compared to men. In traditional office settings, an eight-hour workday is largely unaffected by domestic tasks, whereas WFH allows these responsibilities to overlap with work hours, potentially affecting income and productivity.

To analyze WFH's gendered effects, a difference-in-differences model was applied separately for men and women (Table 7). Findings indicate that: Women's weekly working hours increased by 3.2 h, while the effect on men's hours was positive but not statistically significant. Men's income increased by 15.8%, whereas WFH had a positive but statistically insignificant effect on women's income.

These results suggest that WFH may have widened gender gaps in the Peruvian labor market during the pandemic. Similar patterns have been observed in the U.S., where Wulff and Vernon (2022) found that WFH had a greater positive effect on women's work hours but did not influence gender wage premiums. Arntz *et al*. (2022) found that among parents, WFH reduced gender gaps in hours and earnings but only led to wage increases for fathers—unless mothers switched employers.

The effect of WFH on women's working hours also depends on children's age [9]. As shown in Table 8: Women with children aged 6–16 worked an additional 4.2 h per week due to WFH. Women with children under 6 saw a smaller, statistically insignificant increase of 1.3 h. This suggests that younger children require more care, limiting the increase in working hours for remote-working mothers. In contrast, as children grow older and require less supervision, women can adjust their work hours and income more flexibly with WFH.

6.7 A placebo test

To validate the econometric procedure, we conducted a placebo test using a 2018–2019 sample, one year before WFH was implemented. Due to panel dataset limitations, this sample is smaller than the main estimation. The test assumes that WFH workers in 2020 had already adopted this modality in 2019, designating 2019 as the treatment period and 2018 as the pre-treatment period. We then estimate the DD estimator, applying the same fixed effects as in previous analyses.

Table 7. Double difference estimator by gender of workers with panel data, 2019–2020

	Income			Hours			Income per hour		
	Male (1)	Female (2)	All (3)	Male (4)	Female (5)	All (6)	Male (7)	Female (8)	All (9)
Diff-Diff estimator of WFH	0.158***	0.009	0.086**	1.098	3.213**	2.320**	0.148**	−0.048	0.051
	(0.04)	(0.04)	(0.03)	(1.24)	(1.08)	(0.81)	(0.05)	(0.04)	(0.03)
No. of obs	4,340	2,560	6,900	4,264	2,516	6,780	4,264	2,516	6,780
R-squared	0.836	0.841	0.836	0.722	0.712	0.721	0.795	0.810	0.800

Note(s): *Statistically significant at 10%, **Statistically significant at 5%, ***Statistically significant at 1%. Standard error in parentheses
Source(s): Author's own creation from EHANO panel sample 2019–2020

Table 8. Double difference estimator according to gender of workers and existence of minor children in the home, 2019–2020

	Family: Children with 5–16 years old			Family: Children up to 5 years old		
	Income	Hours	Income per hour	Income	Hours	Income per hour
Men	0.239***	1.306	0.264***	0.184	2.041	0.229
	(0.07)	(1.95)	(0.07)	(0.13)	(3.34)	(0.13)
Woman	0.045	4.210*	−0.048	0.062	−0.052	0.162
	(0.07)	(1.72)	(0.07)	(0.12)	(2.94)	(0.12)
All	0.139**	2.793*	0.107*	0.143	1.158	0.209*
	(0.05)	(1.28)	(0.05)	(0.08)	(2.15)	(0.08)

Note(s): Each coefficient corresponds to a separate regression according to the existence of children of the indicated ages in the household. *Statistically significant at 10%, **Statistically significant at 5%, ***Statistically significant at 1%. Standard error in parentheses
Source(s): Author's own creation from EHANO panel sample 2019–2020

As shown in Table 9, the DD estimator is not statistically significant across the nine indicators examined, confirming that treatment and control groups had equivalent outcomes before 2020.

Theoretical predictions suggest that WFH increases consumption and reduces work hours due to time and resource savings. After adjusting for pandemic-related restrictions, empirical results align with these expectations. The use of multiple fixed effects ensures comparability between groups. This is further supported by: placebo test results, dynamic coefficient analysis, and graphical evidence (Figure 9), confirming parallel trends before WFH implementation. Since WFH is the only distinguishing factor between groups, it is the primary driver of the observed effects.

7. Implications for research and economic policy

This study finds that WFH positively impacts consumption, income, savings, and working hours, enhancing individuals' quality of life by increasing available resources. These effects are significant after accounting for worker characteristics and pandemic-specific conditions. The study's conclusions are grounded in a solid theoretical framework and supported by empirical evidence from a rigorous DD model.

Further studies could explore heterogeneity among workers, as research on WFH in developing economies remains limited. Examining post-pandemic WFH trends would help generalize findings beyond crisis conditions. Additionally, analyzing similar economies—such as Colombia, Chile, and Argentina—could provide broader insights into WFH's effects.

While this study offers a static analysis of WFH's direct effects, a dynamic general equilibrium model with heterogeneous agents could capture long-term impacts on consumption, savings, and workforce segmentation. Given WFH's growing role, such an approach is highly relevant. Future research should also examine WFH's implications for informal economies, low-productivity workers, overregulated labor markets, gig work, hybrid models, and irregular schedules, as these trends will shape the future of work in developing economies.

7.1 Policy implications and limitations

WFH, driven by technological advancements, has economic and non-economic policy implications that require careful assessment. Policies supporting WFH align with efforts to enhance consumption and well-being, but labor regulations must adapt to balance its benefits with emerging costs and responsibilities for employers and employees.

Table 9. Double difference estimator for the 9 indicators with 2018–2019 data (placebo test)

	Main job			All jobs					
	Income (1)	Hours (2)	Income/Hours (3)	Income (4)	Hours (5)	Income/Hours (6)	Income (7)	Consumption (8)	Saving (9)
Diff-Diff estimator of WFH	0.013 (0.03)	−1.122 (0.97)	0.056 (0.04)	0.013 (0.03)	−1.162 (1.04)	0.056 (0.04)	0.021 (0.02)	−0.006 (0.01)	0.014 (0.02)
No. of obs	3,472	3,424	3,424	3,472	3,472	3,472	3,472	3,472	3,472
R-squared	0.849	0.751	0.823	0.852	0.732	0.825	0.925	0.965	0.677

Note(s): The placebo sample considers 2018 as the pretreatment period and 2019 as the treatment period. *Statistically significant at 10%, **Statistically significant at 5%, ***Statistically significant at 1%. Standard error in parentheses
Source(s): Author's own creation from EHANO panel sample 2018–2020

This study has limitations: it relies on a quasi-experimental design rather than a randomized experiment, and its findings are specific to the pandemic period. Future research should explore alternative identification strategies for long-term WFH adoption and address savings, labor market rigidities, and informality to improve applicability and robustness.

8. Conclusion

Initially limited to a few sectors, WFH expanded significantly during the pandemic and remains prevalent, posing ongoing labor market challenges. In Peru, WFH was formally introduced in 2007, surged in 2020, and has slightly declined since, now accounting for 9.5% of dependent workers.

Our proposed model predicts that WFH reduces work hours while increasing consumption and welfare. Empirical data from the ENAHO 2019–2020 panel shows that remote workers work 2,3 more hours per week and earn 6.6% more, likely due to productivity gains or reduced income loss. However, WFH has exacerbated gender gaps: it increases men's income while allowing women—especially those with young children—to work more hours.

WFH also influences consumption. While theoretically expected to boost spending by reducing commuting costs, pandemic-era restrictions led to lower per capita consumption, except among high-income workers who faced fewer constraints. Despite this, remote workers largely maintained consumption levels, supporting the weak permanent income hypothesis. The double difference estimator finds that WFH increases savings by 11.6%, with results remaining robust across analyses.

Overall, the paper emphasizes that WFH has a positive impact on consumption, income, savings, and working hours. The findings suggest that WFH enhances individuals' quality of life by increasing resources that support both consumption and income. These effects are significant after accounting for worker characteristics and conditions specific to the COVID-19 pandemic.

Notes

1. The term WFH has various connotations, including teleworking, remote work, hybrid work, virtual work, etc.
2. According to Eurostat data, in 2020, 12.3% of people were in this mode in the European Union. By country, the highest in Finland (25.1%), Luxembourg (23.1%), Ireland (21.5%), Austria (18.1%) and the Netherlands (17.8%) and the lowest in Bulgaria (1.2%), Romania (2.5%), Croatia (3.1%), Hungary (3.6%) and Latvia (4.5%).
3. The cost savings from WFH benefit both employees and employers. Employers can reduce expenses on office rent, utilities, parking, equipment, furniture, and supplies. Employees save on commuting, work attire, and meals outside the home, among other costs.
4. This corresponds to a daily transportation cost of S/10. The minimum wage is S/1,025, which corresponds to a daily minimum wage of S/48.8 (for a worker who works 5 days a week and 4.2 weeks a month). It is a lower bound since the daily transportation cost varies between S/10 and 20 according to L*uz Ámbar.*
5. After 2020, the exogeneity of pandemic-driven WFH may weaken, potentially limiting this study's methodology. Assessing WFH effects beyond 2020 would require an alternative exogenous instrument or identification strategy. However, since the key advantages of WFH—such as time and resource savings—remain consistent, the effects of transitioning from OW to WFH should align with this study's findings when analyzed with an appropriate methodology. Thus, the study's implications remain relevant, even as WFH shifts from a necessity to a choice in the labor market.
6. For the fixed effects regression of per capita savings, the per capita savings rate is measured as income minus expenditure as a percentage of income.
7. Forbes (2023), The Economist (2021).

8. International studies suggest that during the pandemic female employment has deteriorated to a greater extent than male employment (EIGE, 2021; Eurofound, 2022; ILO, 2021).
9. We consider household children by age range rather than each worker's children, as ENAHO only identifies the children of household heads, making it impossible to track all workers' children individually.

References

Arntz, M., Yahmed, S. and Berlingieri, F. (2022), "Working from home, hours worked and wages: heterogeneity by gender and parenthood", *Labour Economics*, Vol. 76, 102169, doi: 10.1016/j.labeco.2022.102169.

Awada, M., Lucas, G., Becerik-Gerber, B. and Roll, S. (2021), "Working from home during the COVID-19 pandemic: impact on office worker productivity and work experience", *Work*, Vol. 69 No. 4, pp. 1171-1189, doi: 10.3233/wor-210301.

Barrero, J., Bloom, N. and Davis, S. (2020), "60 million fewer commuting hours per day: how americans use time saved by working from home", Working Paper No. 2020-132, University of Chicago, Chicago.

Barrero, J., Bloom, N. and Davis, S. (2021), "Why working from home will stick", Working Paper 28731, National Bureau of Economic Research, Cambridge, MA.

Bloom, N. (2020), *How Working from Home Works Out*, Institute for Economic Policy Research, Stanford.

Bloom, N., Liang, J., Roberts, J. and Ying, Z. (2015), "Does working from home work? Evidence from a Chinese experiment", *Quarterly Journal of Economics*, Vol. 130 No. 1, pp. 165-218, doi: 10.1093/qje/qju032.

Céspedes, N. and Talledo, M. (2024), *Choques económicos y estrategias de suavizamiento de consumo de los hogares*, Documento de Trabajo BCRP, Lima.

Delventhal, M., Kwon, E. and Parkhomenko, A. (2022), "How do cities change when we work from home?", *Journal of Urban Economics*, Vol. 127, 103331, doi: 10.1016/j.jue.2021.103331.

Eliasson, J., Savemark, C. and Franklin, J. (2020), "The impact of land-use effects in infrastructure appraisal", *Transportation Research Part A: Policy and Practice*, Vol. 141, pp. 262-276, doi: 10.1016/j.tra.2020.09.026.

European Institute for Gender Equality-EIGE (2021), "Gender equality and the socio-economic impact of the COVID-19 pandemic".

European Foundation for the Improvement of Living and Working Conditions-Eurofound (2022), "COVID-19 pandemic and the gender divide at work and home".

Forbes India (2023), "Women prefer working remotely, even if it means turning down a dream job. august 2023".

Gimenez-Nadal, J. and Molina, J. (2016), "Commuting time and household responsibilities: evidence using propensity score matching", *Journal of Regional Science*, Vol. 56 No. 2, pp. 332-359, doi: 10.1111/jors.12243.

Guler, M., Guler, K., Guneser Gulec, M. and Ozdoglar, E. (2021), "Working from home during a pandemic: investigation of the impact of COVID-19 on employee health and productivity", *Journal of Occupational and Environmental Medicine*, Vol. 63 No. 9, pp. 731-741, doi: 10.1097/jom.0000000000002277.

Hansen, S., Lambert, P., Bloom, N., Davis, S., Sadun, R. and Taska, B. (2023), "Remote work across jobs, companies, and space", IZA Discussion Paper No. 15980, Bonn.

Heblich, S., Redding, S.J. and Sturm, D. (2020), "The making of the modern metropolis: evidence from London", *Quarterly Journal of Economics*, Vol. 135 No. 4, pp. 2059-2133, doi: 10.1093/qje/qjaa014.

International Labor Organization (2020), *Working from Home: Estimating the Worldwide Potential*, ILO Policy Brief, Geneva.

International Labor Organization (2021), "Working from home: from invisibility to decent work".

Kahneman, D. and Krueger, A. (2006), "Developments in the measurement of subjective well-being", *The Journal of Economic Perspectives*, Vol. 20 No. 1, pp. 3-24, doi: 10.1257/089533006776526030.

Kahneman, D., Krueger, A., Schkade, D., Schwarz, N. and Stone, A. (2004), "A survey method for characterizing daily life experience: the day reconstruction method", *Science*, Vol. 306 No. 5702, pp. 1776-1780, doi: 10.1126/science.1103572.

Koslowsky, M., Kluger, A. and Reich, M. (1995), *Commuting Stress: Causes, Effects, and Methods of Coping*, Plenum Press, New York.

Meng, X. (2003), "Unemployment, consumption smoothing, and precautionary saving in urban China", *Journal of Comparative Economics*, Vol. 31 No. 1, pp. 465-485, doi: 10.1016/s0147-5967(03)00069-6.

Paxson, C. (1992), "Using weather variability to estimate the response of savings to transitory income", *The American Economic Review*, Vol. 82 No. 1, pp. 15-33.

Serebrisky, T., Ancor, S. and Rivas, M. (2019), *Stylized Urban Transportation Facts in Latin America and the Caribbean*, Technical Note No IDB-TN-1 640, Inter-American Development Bank, Washington, DC.

Stone, A. and Schneider, S. (2016), "Commuting episodes in the United States: their correlates with experiential wellbeing from the American time use survey", *Transportation Research Part F: Traffic Psychology and Behaviour*, Vol. 42 No. 1, pp. 117-124, doi: 10.1016/j.trf.2016.07.004.

Stutzer, A. and Frey, B. (2008), "Stress that doesn't pay: the commuting paradox", *The Scandinavian Journal of Economics*, Vol. 110 No. 2, pp. 339-366, doi: 10.1111/j.1467-9442.2008.00542.x.

The Economist (2021), "Why women need the office", August 2021.

U.S. Census Bureau (2023), *American Community Survey, 1-Year Estimates*, TableS0801.

Van Ommeren, J. and Fosgerau, M. (2009), "Workers' marginal costs of commuting", *Journal of Urban Economics*, Vol. 65 No. 1, pp. 38-47, doi: 10.1016/j.jue.2008.08.001.

Wulff, S. and Vernon, V. (2022), "Telework, wages, and time use in the United States", *Review of Economics of the Household*, Vol. 20 No. 3, pp. 687-734, doi: 10.1007/s11150-022-09601-1.

Further reading

Saavedra, J. and Torero, M. (2004), "Labor market reforms and their impact over formal labor demand and job market turnover. The case of Peru. NBER chapters", in *Law and Employment: Lessons from Latin America and the Caribbean*, pp. 131-182.

Supplementary material

The supplementary material for this article can be found online.

Corresponding author

Nikita Céspedes-Reynaga can be contacted at: nikitacr@gmail.com