Telework Exposure and Female Labor Supply in Emerging Economies: Evidence from India

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September 9, 2026

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Abstract

In many emerging economies like India, social norms discourage women from working outside their homes and female labor force participation has remained low for decades. Jobs are often performed at employer's premises, and hence paid labor requires commute and onsite schedule conflict with unpaid household responsibilities. Telework relaxes this constraint: it allows workers to supply paid labor without being physically present. This paper examines whether female labor supply is higher in emerging economy labor markets with more telework compatible jobs. Since India does not have task surveys like O*NET in the United States, I utilize information from the detailed national occupation manual to determine telework scores for each occupation. I define telework exposure as the interaction between pre-existing share of telework-compatible jobs and local digital infrastructure in each district. Using the instrumental variable approach, key results show that a one-standard-deviation increase in telework exposure raises female labor supply by 8.46 percentage points. These gains are concentrated among women who are married, belong to upper caste and economically better off households. Among married women, the effects are skewed towards those who live in nuclear households and have young children. College degrees matter only among women in their late thirties. Cost benefit analysis shows that the public investment in digital connectivity can further unlock women's gains from telework.

Keywords: Labor supply, women, telework, flexible jobs, digital infrastructure

JEL Codes: J16, J22, J81, O33, L96

*. I am thankful to my advisors, Prof. Kara Reynolds, Prof. Mary E. Hansen, and Prof. Austin Davis for their invaluable feedback and guidance. I am also grateful to Prof. Emma Harrington, Prof. Ilaria D'Angelis, Prof. Kyle Schirmann, and Dr. Farah Tasneem for their helpful comments and suggestions. I am grateful for support from the Department of Economics and the Department of Politics, Governance & Economics at American University. All remaining errors are my own.

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1 Introduction

After nearly two decades of decline, female labor force participation (FLFP) in India has begun to recover. Between 2017 and 2024, female labor supply rose by 19 percentage points (Figure 1). While much of this increase is concentrated in self employment (Periodic Labor Force Survey (PLFS), 2024), India also experienced a rise in its online workforce around the same time. Towards the end of 2016, Reliance Jio, an Indian telecommunications company, announced free 4G data, voice calls and other app services to all its users until March 31, 2017. This low cost 4G wireless broadband rollout added 150 million wireless subscribers within a year (Reliance Jio Infocomm Limited 2018). Digital work followed: By 2020, India accounted for roughly one-quarter of the global online workforce. Women represented 28% of Indian online workers (Stephany et al. 2021a). Access to the internet and digital devices increases female labor supply in India by 23% (Fernandez, Prakash, and Puri 2024). This raises the question of whether women are more likely to participate in the labor market when both pieces fall into place: jobs with high telework potential, and sound local digital infrastructure.

A growing literature shows that teleworking and hybrid work arrangements relax constraints on women's paid labor supply. Women tend to place high value on flexible occupations and are more likely to be employed in jobs with higher potential for remote work (Bang 2021; Garro-Marín, Thakral, and Tô 2025). Remote work reduces commuting time and gives workers more flexibility over time allocation (Bryan and Sevilla 2017; Mas and Pallais 2017; José María Barrero, Bloom, and S. J. Davis 2023; Jose Maria Barrero, Bloom, and S. Davis 2021). Particularly, mothers of young children value their ability to work from home (Aksoy et al. 2022; Mas and Pallais 2017; Heggeness and Suri 2021). Previous evidence shows that remote work reduces the motherhood penalty in advanced economies (Arntz, Ben Yahmed, and Berlingieri 2022; Harrington and M. E. Kahn 2026; Mas and Pallais 2017; Bang 2021). Existing studies show that telework protects women from jobloss during the pandemic in the United States and the United Kingdom (Heggeness and Suri 2021; Hupkau and Petrongolo 2020). A recent study finds that telework increased mothers' labor supply after the COVID-19 pandemic in United States (Song 2026).

However, evidence is still limited in emerging economies, where social norms are more binding on women's labor supply than in advanced economies. Two recent randomized controlled trials in two Indian cities show that women prefer remote working arrangements (Jalota and Ho 2024; Ho, Jalota, and Karandikar 2024). However, these interventions focus on less productive forms of work, such as digital gig work, that are randomly assigned to women from low-income households. In Latin America, telework attenuated employment loss for mothers of young children during the pandemic and reduced the child penalty (Berniell et al. 2023; Zarate 2025). Yet less is known about whether greater exposure to telework in the local labor market translates into higher female labor supply in emerging economies.

In this paper, I examine whether women increase their paid labor supply when their local labor market becomes more exposed to telework. This country provides an ideal setting to study this question because its low FLFP is strongly intertwined with entrenched gendered norms. India places high value on women's "purity" reputation, unpaid household responsibilities and discourage their interaction with men outside their families (Jayachandran 2020; Dean and Jayachandran 2019; Muñoz Boudet et al. 2013).[1] This suggests that women's labor supply depends on whether the local economy offers jobs that can be done without violating with social norms and mobility. I show that a one-standard-deviation increase in telework exposure raises female labor force participation by nearly 3 percentage points. On the contrary, the effect of telework exposure on men's labor supply is negligible. The results using an instrumental variable approach also point in the same direction. The two-stage least squares estimate shows that a one-standard-deviation increase in telework exposure increases women's participation by 8.46 percentage points. This accounts for nearly one-third of the average female labor force participation during 2017-2024.[2] These effects mainly operate through three channels: (i) women who are married, have young children and come from nuclear families; (ii) women who come from households with advantageous socioeconomic conditions; and (iii) women with college education in their late thirties.

A central contribution of this paper is the construction of a novel measure of telework exposure. A growing literature focuses on the construction of remote or telework scores (Dingel and Neiman 2020; Hansen et al. 2023; Adrjan et al. 2025). Majority of the studies working on remote work potential and labor market consequences map occupations with their telework compatibility scores using Dingel and Neiman (2020) which draws on O*NET survey in United States (Heggeness and Suri 2021; Song 2026; Basso et al. 2026; Amuedo-Dorantes et al. 2023; Beauregard et al. 2022; Hupkau and Petrongolo 2020).

1. This is especially true in upper caste households which usually have high income levels (Jayachandran 2020; Klasen and Pieters 2015; Klasen 2019; Mehrotra and Parida 2017; Deshpande 2025)

2. Using Indian labor force surveys, the average female labor force participation is 28.7%

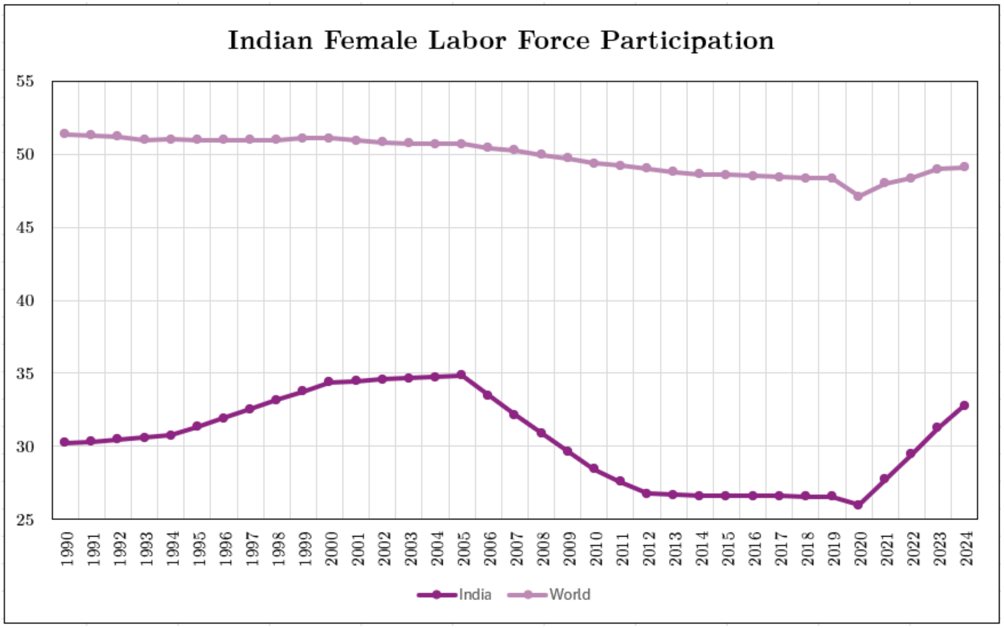


Figure 1. Female Labor Force Participation Trends in India (1990-2024).

However, applying U.S.-based telework classifications to other countries, especially emerging economies, can introduce measurement error through crosswalks and context-specific differences in job tasks (Blázquez, Herrarte, and Moro-Egido 2023; Dingel and Neiman 2020). Since India does not have a task survey like O*NET, I utilize a supervised text classification approach to identify the telework potential of each occupation from the detailed national occupation classification. I manually label a training sample of detailed NCO occupations and use text-based classification methods to predict whether each occupation can plausibly be performed remotely or in hybrid work arrangements. This framework can be applied in other countries where task-based surveys are unavailable but they have high potential to explore impacts of remote work. In this paper, I combine shares of telework-compatible jobs with local digital infrastructure to construct *realized* exposure to telework and hybrid opportunities in each district.

Since digital infrastructure is likely to be correlated with district-level development trends, the telework exposure can be endogenous. Mobile operators may expand networks in areas with high demand for telecom infrastructure. These include districts with rapid urbanization, faster economic growth and higher demand for digital services–all of which can shape women's paid labor supply. I use an instrumental variable strategy that exploits India's rapid expansion of cheap 4G internet starting in 2016. The instrument leverages terrain-driven wireless signal strength to capture district-level gains from this rollout. This approach isolates the geographic variation in signal quality which solves the endogeneity problem from actual cell tower placement. Specifically, I use the Longley-Rice Irregular Terrain Model (ITM) to predict how natural obstacles like mountains and hills block or enhance radio signals across districts.

To the best of my knowledge, this paper is one of the first to provide nationally representative evidence on how the expansion of telework exposure affects female labor force participation in an emerging economy. It contributes to several strands of the literature. Firstly, this paper contributes to the literature on the determinants of women's labor supply in emerging economies. Previous studies have shown that household income, marriage, childcare, and digital access influence women's participation in the labor market (Klasen and Pieters 2015; Klasen 2019; Mehrotra and Parida 2017; Jayachandran 2020; Deshpande 2025; Kusumawardhani et al. 2023a). These constraints are further compounded by social norms which stigmatize working outside home (Jayachandran 2020; Dean and Jayachandran 2019; Muñoz Boudet et al. 2013). I contribute to this literature by showing that greater exposure to telework-compatible occupations increases female labor supply by relaxing social norms regarding women's paid labor.

Secondly, this paper contributes to the growing studies on the relationship between telework/hybrid work arrangements and women's outcomes (Emanuel and Harrington 2024; Harrington and M. E. Kahn 2026; Berniell et al. 2023; Zarate 2025; Song 2026; Arntz, Ben Yahmed, and Berlingieri 2022; Bang 2021; Mas and Pallais 2017; Heggeness and Suri 2021; Hupkau and Petrongolo 2020; José María Barrero, Bloom, and S. J. Davis 2023; Aksoy et al. 2022). Majority of these studies have focused on child penalty in developed countries. I extend this literature by providing new evidence that women are more likely to participate in paid labor if local labor market is more exposed to telework-compatible opportunities and that the effect is stronger among women with young children. Lastly, this paper also adds to the growing literature on digital access and labor market consequences (Hjort and Poulsen 2019a; Ngai and Petrongolo 2017; Viollaz and Winkler 2022; Dettling 2017a; Zuo 2021; Akerman, Gaarder, and Mogstad 2015; Kusumawardhani et al. 2023b). There exists limited literature on the causal effects of internet access on female labor supply (Dettling 2017b; Kusumawardhani et al. 2023b). I contribute to this literature by documenting that digital connectivity increases female labor supply through telework-compatible occupations.

The rest of the paper is organized as follows. Section 2 gives the institutional context about telework and digital infrastructure in India. Section 3 introduces a theoretical framework which derives conditions under which a woman chooses between not working, teleworking and in-person working. Section 4 describes the data and construction of telework exposure. Section 5 describes the empirical strategy. Section 6 presents the results which includes baseline findings, heterogeneous effects and robustness checks. Section 7 presents cost benefit analysis of public investment in digital infrastructure. Section 8 concludes.

2 Indian Context

2.1 Cell Tower and Internet Access

Over the past two decades, India experienced a remarkable growth in telecommunications infrastructure. Cell towers increased from 250,000 in 2007 to 817,000 in 2024 (Ernst & Young LLP and Tower and Infrastructure Providers Association 2020; Department of Telecommunications, Government of India 2025b). This could be attributable to combination of three distinct events: first was the emergence of Towercos, private companies responsible to build and maintain cell towers since August 2000. These independent tower companies (Provider Category-I (IP-I)) could lease macro towers, poles, duct space and dark fiber to multiple licensed telecommunication operators (Department of Telecommunications, Government of India 2025a). As a result, 84 percent of towers in India are managed by Towercos (Houngbonon, Rossotto, and Strusani 2021).[3] In 2008, the Department of Telecoms permitted and laid out guidelines for "active sharing" of telecom infrastructure (Telecom Regulatory Authority of India 2007). This means that the mobile operator companies could install their own antennas and other network equipments on the macro infrastructures. This drastically reduced capital expenditure of mobile network operators and they aggressively expanded their penetration across telecom circles.

The second turning point was the expansion of low-cost wireless broadband internet in 2016-17. The second turning point was the cheap wireless broadband internet in 2016-17. Reliance Jio, a telecommunication company, launched its 4G service on September 2016. During its promotional period, it gave all users free and unlimited 4G data, voice and video calls until December 2016. This intensified competition between all incumbent operators and shift from 2G/3G towards 4G (Reliance Industries Limited 2016; Telecom Regulatory Authority of India 2019b).

3. Only China surpassed India: nearly 100% towers are managed by the Towercos. In comparison, 70% of towers in US and Canada were built and managed by Towercos.

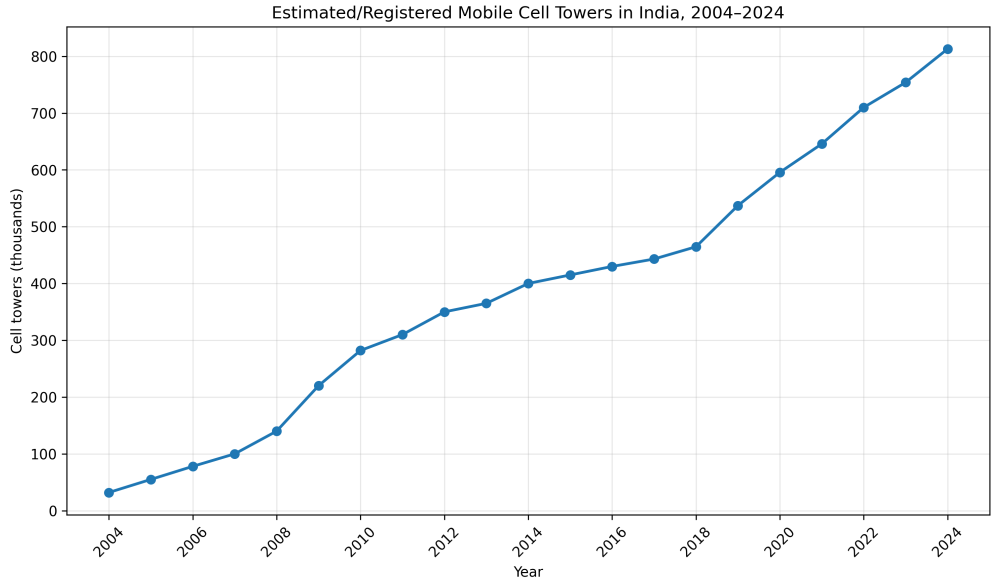
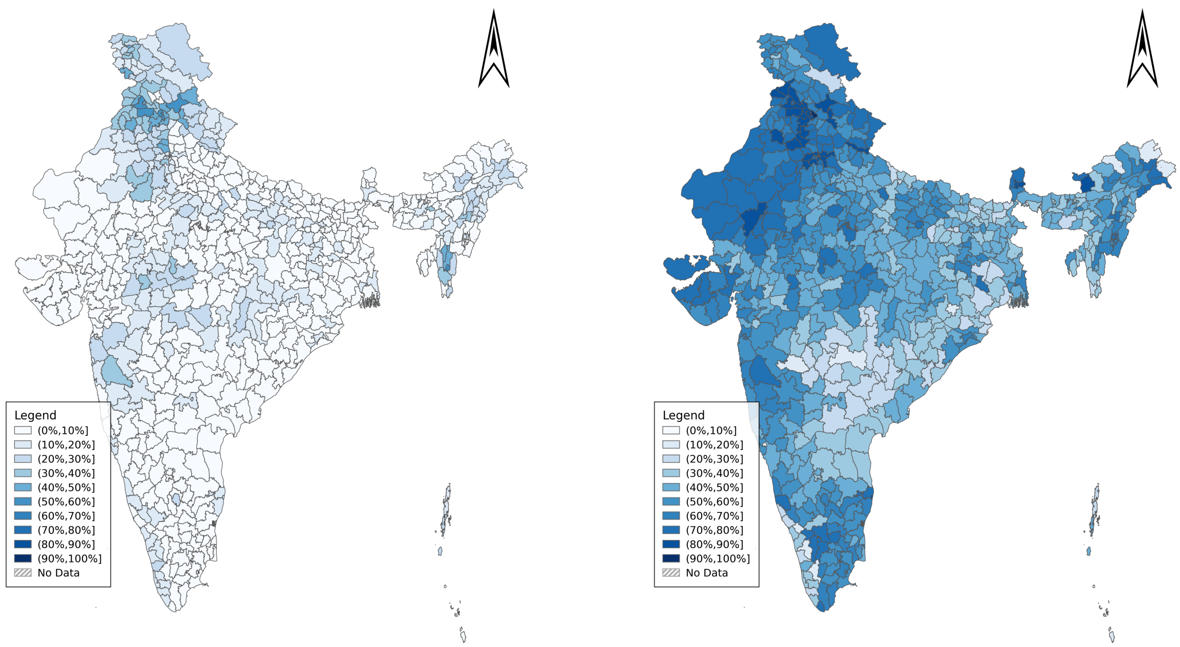


Figure 2. Cell Tower Trends in India (2004-2024). *Source:* Department of Telecommunications, *Telecom Statistics India 2024*. Figures are measured as of March 31 of each year.

The average wireless-data tariff declined by 91.5% from $3.53 per GB in 2015 to $0.30 in 2017, while average monthly data use per active subscriber increased from 1.18 GB in 2016 to 7.69 GB in 2018 (Telecom Regulatory Authority of India 2019b). By 2018, 4G accounted for nearly 87 percent of wireless-data consumption. According to the National Family Health Survey (NFHS), the share of households with internet access increased from 10.52% in 2015-16 to 49.9% in 2019-21. Figure 3 shows that the distribution of households with internet access across Indian districts.

The expansion of 4G also improved the ability of mobile networks to support online work. Although mobile speeds remained lower in India than many advanced economies, they were capable to support web browsing, email, platform messaging, coding, content writing, data entry, and periodic file transfers. A computer can be connected through a mobile-phone hotspot, a cellular router, or a USB dongle to establish connectivity where fixed lines are unavailable (International Telecommunication Union 2011; BroadbandNow 2026). In absence of fixed broadband connection, this allowed workers to rely on mobile data infrastructure to perform online work (World Bank and International Telecommunication Union, ITU DataHub: Price of High Usage Voice and Data Bundles). In 2019, average mobile download speed increased to 11.5 Mbps from nearly 8.9 Mbps in December 2017 (Nokia 2020). In March 2019, India had approximately 615 million wireless internet subscriptions (Telecom Regulatory Authority of India 2019a).

While Reliance Jio also introduced fibre-to-the-home (FTTH) in 2019, most consumers saw no immediate reason to buy home Wi-Fi when cheap mobile 4G data satisfied their daily needs. The third paradigm shift arrived with the 2020 COVID-19 lockdown. The 2020 lockdown compelled firms to transition their daily operations to virtual platforms which induced massive adoption of video conferencing and virtual collaboration tools. This triggered exponential surge in wired internet subscription by 18.61% within a single fiscal year from 19.18 million in 2019.



(a) Households with internet access (2015-16) **(b)** Households with internet access (2019-21)

Figure 3. Household-level Internet access across Indian districts. *Source: National Family Health Survey (2015-16 to 2019-21).*

2.2 Expansion of Telework and Hybrid Work Arrangements

Telework existed in India before the COVID-19 pandemic in 2020 but it was not widely adopted. Pre-pandemic remote work was primarily visible in information technology (IT), software services, business-process management (BPM), freelancing, and consulting (Kathuria et al. 2017; Stephany et al. 2021a). By 2016, one-third of Indian IT-BPM workforce were women (NASSCOM and PricewaterhouseCoopers Private Limited 2016). India accounted for 25% of the global online freelance workforce in 2017 (Stephany et al. 2021b). Prior 2020, online freelancing was generally less dependent on continuous group video-conferencing than the large-scale work-from-home arrangements that emerged during the COVID-19 pandemic. Clients and workers frequently communicated through email, telephone calls, platform-based messages, and periodic exchanges of instructions, files, feedback, and completed assignments (Kathuria et al. 2017). Common activities included data-related tasks, content writing, software development, web design, and digital marketing. Although some assignments required real-time communication or availability during specified hours, much of this work was organized around discrete projects and deliverables.

During the COVID-19 pandemic, the IT industry shifted about 90% of its workforce to remote arrangement within a very short period (Agarwal, Mandavia, and Sangani 2020). But this transition was uneven, depending on task characteristics. Employees with client facing tasks (e.g., solution architect, customer service) could not always work remotely from home and other suitable workspace at home. Thus, the 2020 lockdown was accompanied with limited onsite attendance for unavoidable tasks. Nevertheless, firms began moving more towards remote and hybrid work arrangements. HCL Technologies, for example, proposed rotating half of its workforce between home and the office, while the chief executive of Tech Mahindra observed that "work from home does not mean work from home forever" (Agarwal, Mandavia, and Sangani 2020). The institutional basis for remote work was also strengthened in November 2020, when the Department of Telecommunications simplified the regulations governing Other Service Providers and explicitly encouraged both work from home and "work from anywhere" within India (Government of India, Ministry of Communications, Department of Telecommunications 2020). This can be attributable to two reasons: firstly, the hybrid work environment reduced firms' rental, operational overhead and logistic costs; secondly, remote and hybrid arrangements saved commuting time which can save workers 1.47 hours per day to reinvest into their work and personal lives.[4] During 2023-24, several IT firms consolidated minimum office-attendance. In 2024, Cognizant instructed its India-based employees to attend the office an average of three days per week and introduced schedules to balance between remote and office days (Sai Ishwarbharath B 2024). It should be noted that these new work model was mainly available to workers engaged in occupations with high telework potential.

4. In major metropolitan cities like Delhi, Mumbai, Bangalore, Indian professionals, on average, spent 100 minutes daily on commuting(MoveInSync Technology Solutions Pvt. Ltd. 2019) which is nearly double the time spent by US workers. Cutting back on commuting could save nearly 1.47 hours giving workers an average of 1.47 hours back each day to reinvest into their work and personal lives (Indeed 2023; MoveInSync Technology Solutions Pvt. Ltd. 2019).

2.3 Impact on Women

Women freelancers were concentrated in writing and translation and they accounted for one-quarter of Indian remote contractors in software development and technology (Stephany et al. 2021a). ICRIER study suggests that women's participation in online gig work was driven by care work (Kathuria et al. 2017). Women-only employment platforms, for example, *JobsForHer* reported that 66% of its team members were mothers and 70% had resumed their careers after a break. By 2017, another similar platform, *GharseNaukri* registered 450,000 women seeking part-time, work-from-home and freelance jobs (Kathuria et al. 2017). A qualitative study of women IT professionals in India found that women valued telework arrangements but it also depended on their projects and operations involved (Dhar-Bhattacharjee and Dwivedi 2023):

> "*. . . if an individual who gives me the work, I'll finish at home, or if I have the option of working from home, I would be more than happy. . . if I today say that my son is not well, I can't come to the office because I can't leave him in the day care. They give me the option, but my conscience says that I can't give 100% from home, because these operations I have to be looking onto the screens, I have to see what people are around. Are they really seriously doing their work or not? This work, I can't do it from home, being in operations. So, I feel it from inside that I'm not giving 100%, so sometimes, if very often, I need, I will restrict myself not to ask for a work-from-home option.* (Employee, Betex)"

Before the pandemic, some large Indian firms had already introduced flexible schedules, and programs for women returning after career breaks. In 2012, Hindustan Unilever's chief executive described the company's policies as including "flexible working hours, opportunities to work from home, even opportunities to work part-time" (The Economic Times 2012). The company also used project-based assignments to help women resume employment, while IBM combined flexible schedules with workplace childcare (Basu 2012). The Maternity Benefit (Amendment) Act of 2017 formally recognized teleworking for working mothers of young children. Section5(5) states

> *"In case where the nature of work assigned to a woman is of such nature that she may work from home, the employer may allow her to do so after availing of the maternity benefit for such period and on such conditions as the employer and the woman may mutually agree."*

This suggests that women in jobs with higher telework potential could perform remotely, to balance between work and maternal life. By 2018, Viacom18 provided 36 weeks of paid maternity leave followed by 12 weeks of flexible working and allowed work from home during personal emergencies. Ericsson permitted employees to adopt an alternative work schedule for up to three months per year (Singh 2018).

It is apparent that remote or hybrid work arrangements could potentially retain female employees. Fewer commuting and relocation may make formal employment more accessible to women with mobility, safety and childcare costs. But this new work model shed light on inequalities in terms of privacy, time allocation and physical workspace within the household. Chauhan (2022) interviewed 30 dual-earning couples who were remotely working during the pandemic. They found that men's work were viewed with high importance while women faced double burden due to household chores and paid jobs. One-third of the women reported that they lacked own workspace and had to frequently switched rooms to concentrate better:

> *"I don't have proper space to work from home -no work desk, nothing. I and my husband had set up a workstation in our bedroom. We rarely had meetings before, and we would usually opt for work-from-home on separate days. Now all of us are at home all the time. So, he has taken up that work desk permanently. I am mostly in the living room working from my couch. It is really hard to focus. My back hurts sitting on the couch. There are interruptions when I am in my meetings. I have changed my room in between the meetings so many times because my children are usually in the room where I am working. My husband locks the room from the inside when he needs to concentrate. I don't have that liberty. I have no room of my own."*

By December 2020, Deshpande (2022) found that men's average housework hours had fallen below their pre-pandemic level, whereas women's hours had increased sharply. This partly explains why women were eleven times more likely than men to leave jobs after the lockdown was withdrawn (Abraham, Basole, and Kesar 2022).

3 Theoretical Framework

In this section, I present a simple model of a woman's labor supply choice in the presence of teleworking opportunity. The model formally introduces the idea that telework can relax constraints which make in-person jobs costly for women, especially commuting time, and social cost from difficulty in adjusting both domestic and workplace responsibilities. Flexible work arrangements also bear non-pecuniary cost due to emotional exhaustion, frequent interruptions and multitasking (Leroy, Schmidt, and Madjar 2021; Trougakos, Chawla, and McCarthy 2020). A woman chooses among three alternatives: office work, telework, and no paid work. The model generates conditions under which telework is preferred to office work and no paid work.

3.1 Setup

Suppose a woman has a standard preference described by $u(c, \ell, H)$, where c is consumption, ℓ is leisure and H is home production. Home production depends on time spent on domestic work d and available home technology θ:

$$H = f(\theta, d), \qquad f'() > 0, \quad f''() < 0. \tag{1}$$

A woman can choose among three alternatives, indexed by

$$r \in \{O, T, N\},$$

She also gets disutility $v(L)$ which rises by a constant factor τ_r, depending on whether she is working in-person (τ_o) or teleworking (τ_T).

Her budget constraint is given by $c = y_h + w_r L$, where y_h is (fixed) husband's income, w_r is wage rate for corresponding r choice ($w_N = 0$) and L is paid labor. For simplicity, I assume that total time worked and spent on leisure remains same under flexible work or in-person arrangements. That is, $\ell_r = \ell$ and $L_r = L$. This implies the adjustment comes through change in domestic labor time. Also, I define her overall time constraint as $d_r + \ell + (1 + t_r)L = 1$, where d_r is time spent on unpaid household work under work arrangement r, t_r is commuting cost, that is, $t_o > 0$ and $t_T = 0$.

The value function from choosing r is given by:

$$V_r = \max_{c,\ell,d_r,L} \left\{ u(c, \ell, f(\theta, d_r)) - (1 + \tau_r)v(L) - \phi z(d_r) \right\} \tag{2}$$

subject to

$$c_r = y_h + w_r L, \tag{3}$$

$$\ell = 1 - d_r - (1 + t_r)L \tag{4}$$

Propostion 1. Optimal labor supply under work arrangement r is given by:

$$u_\ell(1+t_r)+(1+\tau_r)v'(L)=u_c w_r \tag{5}$$

For $r \epsilon (O,T)$,

$$t_o u_\ell+(\tau_o-\tau_T)v'(L)=u_c(w_o-w_T) \tag{6}$$

where u_c measures marginal utility from consumption, u_ℓ is marginal utility from leisure and $v'(L)$ is marginal disutility from paid work.

This shows that a woman supplies paid labor until the marginal utility gain from earnings ($u_c w_r$) equals to the marginal cost from working. For every additional unit of paid labor time, a woman gives up on gains from leisure (u_ℓ), bears commuting cost ($t_r u_\ell$) as well as non-pecuniary cost of working ($\tau_r v'(L)$), apart from marginal disutility from working itself ($v'(L)$). It also suggests that office work must offer a sufficiently higher wage than telework to compensate for its higher time cost ($t_o u_\ell$) and any additional non-pecuniary burden ($(\tau_o - \tau_T)v'(L)$). Conversely, telework becomes more attractive when it reduces commuting time, lowers the non-pecuniary cost of work, or when the wage penalty from telework is small.

3.2 Optimal choice.

The following lemma summarizes the woman's choice problem.

Lemma 1. The woman chooses telework, office work, or no paid work according to the following decision rule:

$$T \text{ is chosen} \iff V_T > \max\{V_O, V_N\}, \tag{7}$$
$$O \text{ is chosen} \iff V_O > \max\{V_T, V_N\}, \tag{8}$$
$$N \text{ is chosen} \iff V_N > \max\{V_T, V_O\}. \tag{9}$$

This framework highlights two factors. First, telework can shift from in-person office work to telework if it reduces commuting and non-pecuniary costs of working. Second, telework can move women from outside labor market to paid labor if the earning gains exceed costs from reducing leisure, reduced home production and any constraints from hybrid working.

3.2.1 Telework versus Office Work

Telework is preferred to office work when

$$V_T > V_O \implies u_c(w_T - w_O)L + u_\ell t_O L + (\tau_O - \tau_T)v(L) - \phi z(d_T) > 0. \tag{10}$$

Equivalently,

$$w_O - w_T < \frac{u_\ell}{u_c} t_O + \frac{(\tau_O - \tau_T)v(L)}{u_c L} - \frac{\phi z(d_T)}{u_c L}. \tag{11}$$

Equation (11) shows that women may prefer telework even when telework pays less than office work. A telework wage penalty is acceptable when telework saves commuting time, and reduces non-pecuniary cost of working. However, telework becomes less attractive when work-from-home frictions are large.

3.2.2 Telework versus No Paid Work

Telework is preferred to no paid work when

$$V_T > V_N. \tag{12}$$

Using the same fixed-hours approximation, telework is preferred to no paid work when

$$u_c w_T L > \tau_T v(L) + \phi z(d_T) - u_H\{f(d_T) - f(d_N)\}. \tag{13}$$

Equation (13) shows that telework draws women into paid work when the additional gain in earnings from telework exceeds additional cost of paid labor. These costs include disutility from working (both paid and unpaid), and net loss in home production ($u_H \Delta f(d)$). Hence, telework is more likely to draw a woman in workforce if cost of home production is not too large.

3.2.3 Office Work versus No Paid Work

Office work is preferred to no paid work when

$$V_O > V_N. \tag{14}$$

Under the fixed-hours approximation, this requires

$$u_c w_O L > \tau_O v(L) + u_\ell(1 + t_O)L + u_H\{f(d_N) - f(d_O)\}. \tag{15}$$

Equivalently, the office wage must be high enough to compensate for the disutility of work, commuting time, the loss of leisure, and the loss of household production:

$$w_O > \frac{\tau_O v(L)}{u_c L} + \frac{u_\ell}{u_c}(1 + t_O) + \frac{u_H\{f(d_N) - f(d_O)\}}{u_c L}. \tag{16}$$

Proposition 2. Empirical Predictions.

The model generates three empirical predictions.

Prediction 1. Telework brings more non-participating women into market when telework wages are sufficiently high, when telework reduces mobility and commuting costs, and when household-production losses from paid work are not too large.

Prediction 2. A woman chooses telework over office work when commuting costs, mobility restrictions, or social costs are high. This follows from equation (11).

Prediction 3. Thus, a woman's labor supply response to telework exposure should be stronger among those who face higher volume of domestic responsibilities, norms on working outside home and/or mobility constraints.

In the empirical analysis, I identify the impact of access to teleworkable opportunities on a woman's participation in labor market.

4 Data and Variables

4.1 Data

Periodic Labor Force Survey (PLFS). I define a participant as being in the labor force if they report either being employed or having sought employment during the seven-day reference period prior to the survey. PLFS defines labor market participation based on their activity status either for the past one year or seven days before the survey took place.[5] It is a nationally representative survey that collects information on employment, income, socioeconomic and demographic characteristics for over 100,000 urban and rural households in India. The survey is conducted annually but organized on a quarterly basis. Currently, PLFS has released seven years of data: July 2017-June 2018, July 2018–June 2019, July 2019–June 2020, July 2020–June 2021, July 2021–June 2022, July 2022-June 2023, July 2023–June 2024. Over these seven rounds, the survey collected information from 709,873

5. In PLFS, labor market outcomes are measured in four different ways: (i) usual principal activity status (UPAS), (ii) usual subsidiary activity status, (iii) current weekly activity status (CWS), and (iv) current daily activity status. UPAS captures an individual's activity status 365 days before the survey. CWS measures activity status during 7 days prior to the survey.

households (390,135 in rural areas and 319,738 in urban areas) for about 2,949,407 individuals (1,698,828 in rural areas and 1,250,579 in urban areas). The sample is based on a stratified multi-stage sampling design, and all the empirical analysis in the paper uses the survey weights provided in the data.[6] I restrict the sample to individuals aged over 18 years and utilize all rural and urban households during the first visit. This leaves us with a sample of 1,959,066 individuals covering all the 646 Indian districts.

Table 1 presents summary statistics of adult men and women using the seven rounds of PLFS data (2017-2024).The labor force participation rate for women is 52.6 percentage points lower than that of men. Similar trends are observed for men and women who are employed: the gender gap in employment is 39 percentage points. On average, women report 10.0 hours of paid labor per week while men spends 37 hours per week in jobs. Furthermore, women are 59.3 percentage points more likely to spend exclusively in unpaid household responsibilities than men. Figure 4 shows that majority of surveyed women are married (74%). Panels 4b and 4c show that majority of women come from ethnically advantageous and upper caste households.

6. The sampling weights adjust for unequal probabilities of selection caused by its stratified multi-stage design. The NSS ogranization provides a base multiplier at the Second Stage Stratum (SSS) level, which indicates the number of similar population units represented by each sampled unit. In the PLFS data, NSSO releases separate sub-sample multipliers, and these need to be adjusted to construct the final weight for combined estimates using both sub-samples. Since NSSO multipliers are reported with two implied decimal places, the multiplier must first be divided by 100. For combined estimates, the final weight is calculated as (MLTS/100) when the number of surveyed First Stage Units (FSUs) in the sub-sample is equal to the number in the combined sub-samples, that is, when (NSS = NSC). However, when the number of surveyed FSUs differs between the sub-sample and the combined sub-samples, that is, when (NSS ≠ NSC), the final weight is calculated as (MLTS/200).

Table 1. Summary Statistics by Gender

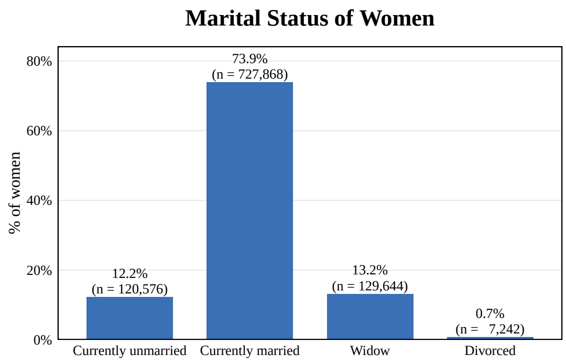
Variable	**Female**	**Male**
Labor force participation	0.287	0.813
	(0.0005)	(0.0004)
Employment participation	0.266	0.760
	(0.0004)	(0.0004)
Weekly working hours	10.00	37.14
	(18.37)	(24.53)
Only unpaid labor	0.607	0.014
	(0.488)	(0.116)
Age	41.181	40.959
	(0.016)	(0.016)
Weekly wage ($)	36.297	270.827
	(0.246)	(0.803)
Household characteristics		
Dependency ratio	0.310	
Monthly per capita consumption expenditure ($)	27.98	

Notes: The table reports summary statistics for individuals over age 18 in the PLFS. Columns (1) and (2) report means for women and men, respectively, with standard errors in parentheses. Household-level characteristics are reported once because they are common to individuals within the same household. Labor-force participation and employment participation are indicator variables. "Only unpaid labor" identifies individuals who report unpaid domestic work as main activity. The table highlights substantial gender differences in labor-market participation and weekly wages.

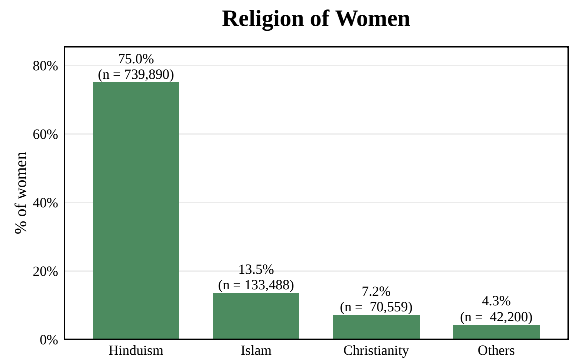
National Classification of Occupations of India (2015, 2004). This is a reference manual that gives detailed information on occupations in the Indian labor market. Published by the Ministry of Labor and Employment, this manual covers occupation title, job descriptions and skill requirements for nearly 3,448 occupations across 52 sectors.[7] NCO–2015 follows an eight-digit hierarchical coding structure: the first digit identifies the broad occupational division, the first two digits the sub-division, the first three digits the occupational group, the first four digits the occupational family, and the subsequent digits distinguish detailed

7. Directorate General of Employment under the Ministry of Labor and Employment, India

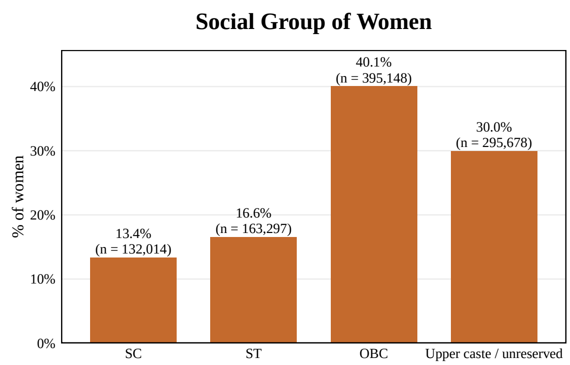
occupations and associated qualification standards.



(a) Marital Status



(b) Religion



(c) Social Group (Official umbrella of castes)

Figure 4. Distribution of Adult Female Population by their marital status, religion and social group using PLFS dataset.

The first four levels are aligned with the major-group, sub-major-group, minor-group, and unit-group structure of ISCO–08.[8] The 8-digit level is primarily used in National Career Service portal to match an employer's open vacancy with an unemployed worker's specific skill set.

Employment and Unemployment Survey. This is a nationally representative household survey that provides information on individuals' employment status, industry, occupation, and other demographic and socioeconomic characteristics. I pool the 2007–08, 2009–10, and 2011–12 rounds to calculate the weighted share of employed individuals in each NCO-2004 three-digit occupational group within each district. Pooling the three rounds increases the number of observations within districts and produces more stable measures of each district's pre-existing occupational structure. I then combine these dis-

8. ISCO-08 stands for International Standard Classification of Occupations, 2008

trict employment shares to use as weights for each teleworkable occupations. I use NCO descriptions to determine teleworkability of each occupation. Details are discussed in the next subsection 4.2.

Digital Infrastructure. The Telecom Regulatory Authority of India (TRAI) typically publishes annual and quarterly data on wired and wireless internet penetration at the telecom-circle level. A telecom circle is a geographic service area designated by the Department of Telecommunications (DoT) for licensing and regulatory purposes. At present, there are 22 telecom circles. However, there is a lack of consistent time-varying internet consumption data at district level. However, time-varying internet consumption data remains unavailable at the sub-regional or district level. While certain household surveys capture localized digital use, these metrics are collected only intermittently (International Institute for Population Sciences and ICF 2022; Ministry of Statistics and Programme Implementation, Government of India 2023). Thus, these traditional sources cannot be utilized to construct an annual district-level panel of digital connectivity. To overcome this limitation, I focus on publicly available data (e.g., OpenCellID) on cell tower counts by latitude and longitude of a location over years.

I use data on cell towers from OpenCellID which is an open-source, partially crowd-created repository of cellular towers.[9] It provides latitude and longitude of mobile tower locations across the world. The database identifies location using cell records instead of physical tower counts. So, the cellular infrastructure includes both macro towers and other cellular installations such as rooftop sites. Because the bulk download on OpenCelliD interface is limited to cells observed during the preceding 18 months, I utilized its historical snapshot for India which is distributed through Kaggle.[10] I find 2.49 million cell tower records using the mobile network across the country. According to the official data, the number of mobile base transceiver stations (BTS) were 2.40 million as of December 9, 2022 (Azam, Emran, and Shilpi 2024).

4.2 Construction of Telework Exposure

A widely used benchmark measure proposed by Dingel and Neiman (2020) uses task-based information from the U.S. O*NET Work Context and Generalized Work Activities surveys to classify occupations according to their remote-work potential. Some studies apply Din-

9. https://www.opencellid.org/

10. Here's the link: https://www.kaggle.com/datasets/sachinxshrivastav/mobile-network-coverage-india

gel and Neiman (2020)'s telework scores to other economies using occupational crosswalks (e.g., Anghel, Cozzolino, and Lacuesta 2020; Palomino, Rodríguez, and Sebastian 2020). But it has two key limitations when applied outside the United States. First, O*NET was designed for the U.S. labor market, and the tasks associated with an occupation may differ across countries with different structural and technological conditions (Blázquez, Herrarte, and Moro-Egido 2023). Second, applying O*NET-based scores to other economies requires multiple occupational crosswalks—from the U.S. Standard Occupational Classification (SOC) system to the International Standard Classification of Occupations (ISCO) and then to national classifications. These conversions are many-to-many and inevitably lead to information loss and measurement error (Blázquez, Herrarte, and Moro-Egido 2023). Some countries are covered by OECD Programme for the International Assessment of Adult Competencies (OECD PIAAC) and World Bank Skills Toward Employability and Productivity (STEP) surveys which are partly useful to analyze job tasks. The advantage of using these data is that it addresses the concerns raised by defining the feasibility of performing a job at home based on the US economic context. Saltiel (2020) used STEP survey data and finds that 5%–23% jobs can be done remotely in developing countries (Saltiel 2020). Yet many emerging countries (e.g., India, China) lack task-based surveys, as shown in Figure 5.

4.2.1 Manual Labeling and Text Classification

Because India lacks its own task-based survey, I instead use text-based information in the occupation manual (NCO, 2015) using a natural language processing model (NLP). I first manually label 250 occupations as (0/1) teleworkable based on whether the tasks described in the NCO 2015 occupation definition can be performed from home without requiring physical presence, operation of machinery, direct in-person service delivery, or outdoor activities. These manually labeled occupations serve as the ground truth for training the text classifier. Next, I estimate the probability that an occupation is teleworkable using a logistic regression text classifier:

$$\Pr(TW_o = 1 \mid x_o) = \Lambda(\alpha + x_o'\beta) \tag{17}$$

where x_o includes textual features extracted from occupation titles and descriptions in the NCO 2015, and $\Lambda(\cdot)$ denotes the logistic function. I create a locked test set of 150 manually labeled occupations which is held out entirely from model training. The objective is to see how well the classifier performs on occupations it has never seen before. I then

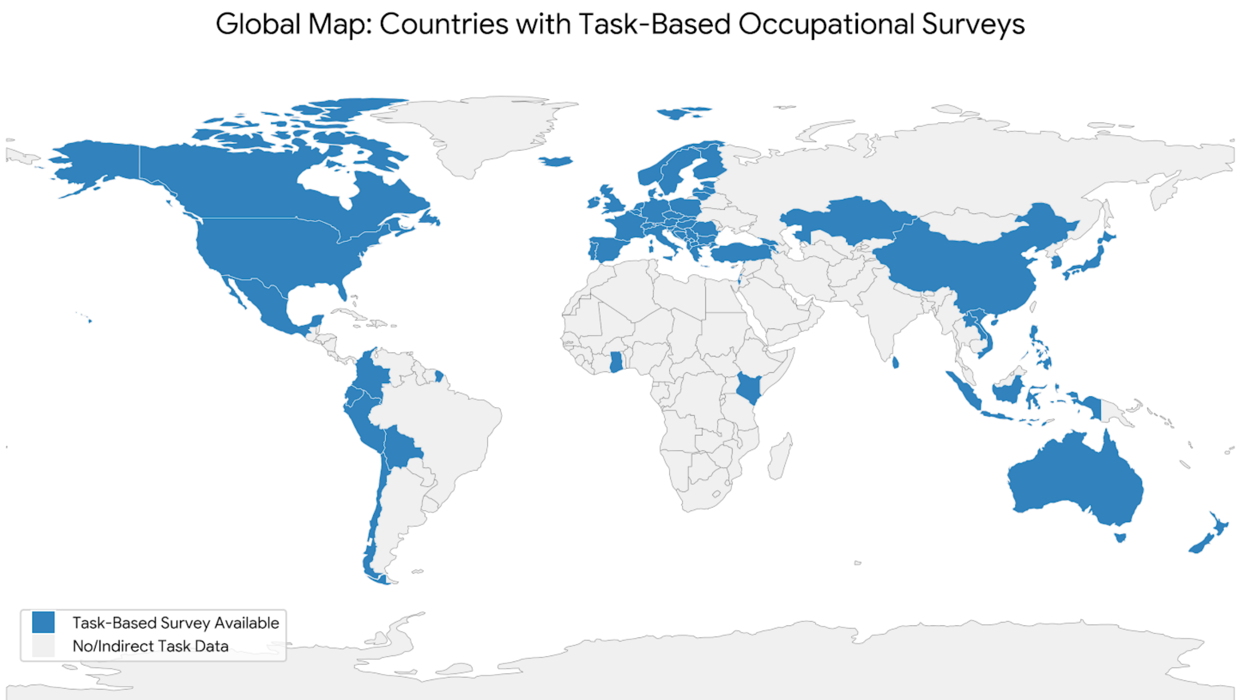


Figure 5. Global coverage of task-based surveys. Countries highlighted in blue have participated in dedicated task-focused surveys (O*NET, PIAAC, STEP, or ESJS) capturing granular skill usage. Note that for middle-income contexts like Ghana, Kenya, and Vietnam, data is sourced from the World Bank STEP program, whereas India currently relies on crosswalks or occupation-manual indices.

apply the fitted classifier to predict telework scores p_o for all remaining unlabeled 8-digit occupations in the NCO 2015. Figure 6 shows the distribution of telework scores. To determine which scores should be classified as teleworkable, I define a threshold, τ by maximizing the F1 score, which trades off false positives and false negatives (Lipton, Elkan, and Naryanaswamy 2014). As a robustness check, I choose τ using Youden's J statistic, which maximizes the sum of true positive rates (sensitivity) and true negative rates (specificity). Both criteria yield a threshold of 0.468 (Table 9, Appendix C.1) with an accuracy of nearly 0.81 (Table 10, Appendix C.1). See Appendix D.2 for details about NLP terms. Using the locked set ($N = 150$), I also construct the confusion matrix to compare the manually assigned values with the model-generated values. The objective is to see how accurately the model predicted teleworkability of occupations. As shown in Table 2, the model achieves an accuracy of 82% accurate predictions (i.e., true negatives and true positives).

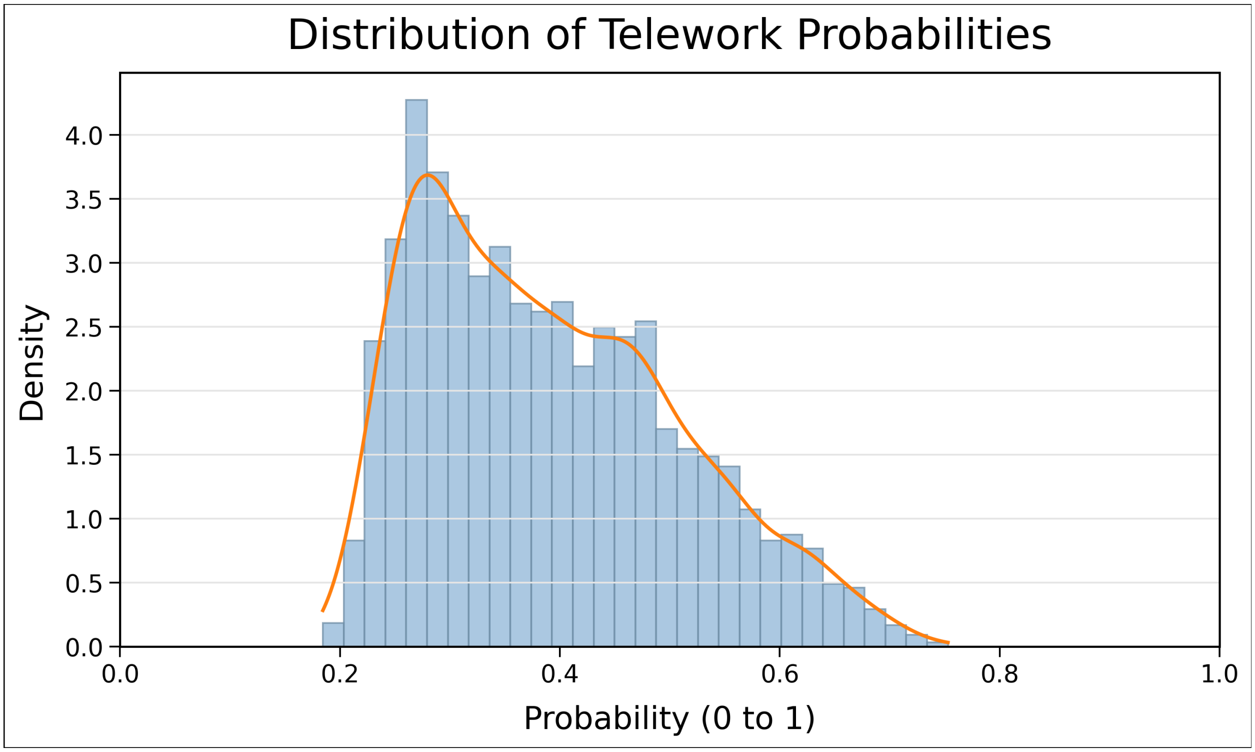


Figure 6. *Distribution of Predicted Probabilities generated using equation (17). The range lies between 0.1845 and 0.7529.*

Manual		ML-generated: 0 (Not teleworkable)	ML-generated: 1 (Teleworkable)
Manual	**0 (Not teleworkable)**	87 (58%)	20 (13.33%)
Manual	**1 (Teleworkable)**	8 (5.33%)	35 (23.33%)

Table 2. Confusion matrix comparing manually generated and ML-generated telework indicator (N = 150).

I classify each 8-digit occupation as teleworkable if its score exceeds the optimal F-1 threshold (i.e., 0.468) which maximizes the balance between false positives and negatives. Table 3 lists ten occupations with highest and lowest predicted telework probabilities. It shows significant variation across occupations. Jobs that heavily rely on digital tools, analytical tasks and computer-based outputs are highly teleworkable ($Pr(TW) > 0.7097$). These include software engineer, product designer, technical writers, management and market researchers. On the contrary, the least teleworkable jobs ($0.1845 < Pr(TW) < 0.1992$) are machine operators and heavy industrial production roles such as slitting machine operator, wood machinist, surface grinder. These jobs were also part of manually labeled training set and Table 3 shows that the model predictions are consistent with manually assigned scores.

Robustness Check

Using a large language model (LLM), I construct an alternative set of telework scores at an occupation level. Specifically, I use the open-source `Llama 3.1 (8b)` with titles and descriptions of 400 randomly selected occupations from NCO (2015) text manual. Then, I create a prompt that instructs the model to generate telework scores $\in [0,1]$ for each 8-digit occupation. Details about the procedure are in Appendix D.2.1. In this sample of 400 occupations, LLM generated telework scores are positively correlated with the baseline NLP scores ($R = 0.6$). This is shown in figure 11 in the Appendix. The limitation of this approach is that the predicted scores are likely to be sensitive to the prompt and model used. Hence, I use the text classifier as the main framework and LLM-based measure as a robustness check. In Appendix C.2, table 11 provides additional evidence by comparing LLM-generated scores of top ten and bottom ten occupations with their corresponding baseline scores. It reports that software engineers, financial analysts, and communication analysts have the highest telework potential. Heavy machine operator and physically intensive jobs, namely, knitting machine operators and road roller mechanics are least teleworkable. Column (4) shows that the corresponding NLP-based scores follow a similar pattern. This indicates that both methods broadly agree on which occupations are more or less teleworkable. Since the labor force survey data report occupations only at the 3-digit level, I calculate the share of teleworkable 8-digit occupations within each 3-digit occupation. Based on this measure, 25.5% of the workforce is in teleworkable jobs during 2022-24. This includes 27.9% of men and 19.9% of women.

District-level Telework Shares

In order to see how prevalent these teleworkable jobs are in each district, I compute the districts weighted average share of teleworkable jobs according to the following equation:

$$TWO_d^{2007-12} = \sum_{k \in \mathcal{K}} \omega_{dk}^{2007-12} T_k, \tag{18}$$

where $TWO_d^{2007-12}$ is the district's predetermined weighted share of teleworkable occupations T_k denotes the teleworkability score of occupation (k), $N_{dk}^{2007-12}$ is the pooled average number of workers in occupation (k) in district–d over 2007–08 to 2011–12 using three rounds of Employment-Unemployment survey (2007-08, 2008-09, and 2011-12), and

$$\omega_{dk}^{2007\text{–}12} = \frac{N_{dk}^{2007\text{–}12}}{\sum_{j\in\mathcal{K}} N_{dj}^{2007\text{–}12}}$$

is occupation (k)'s share of district employment in the pooled pre-period. Figure 7 shows the share of teleworkable jobs by districts across India.

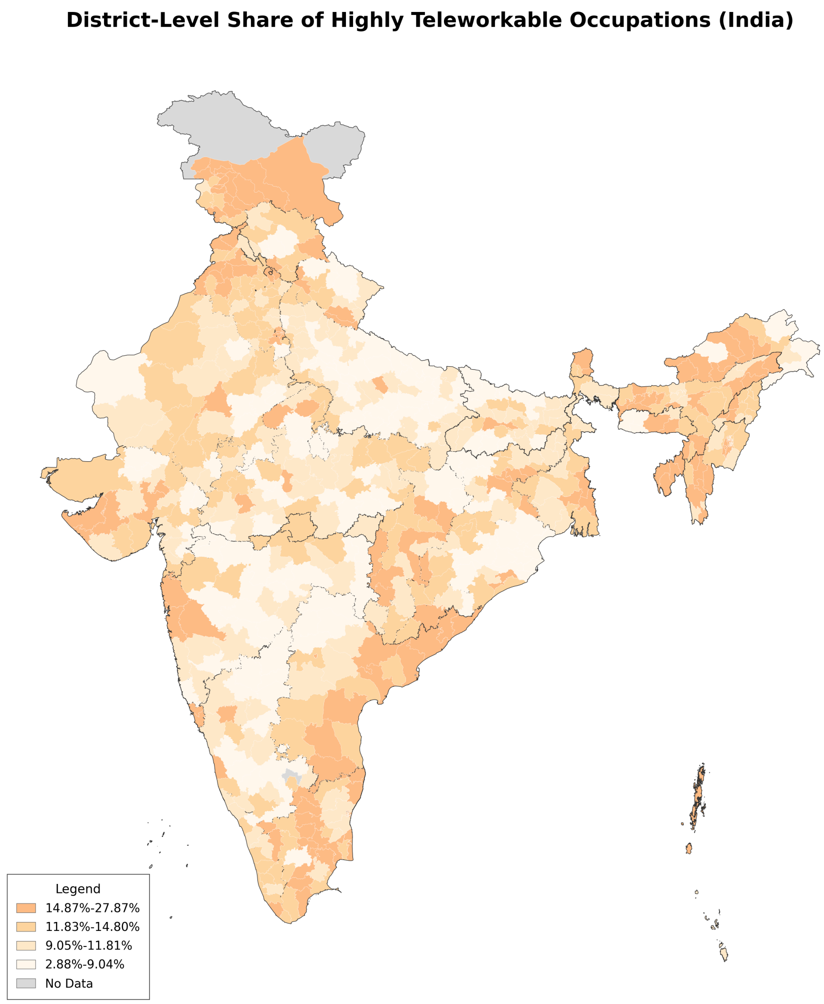


Figure 7. District-wise shares of teleworkable occupations.
Notes: The map shows the district-level share of employment in telework-compatible occupations. Darker the shades, higher is the share of telework-compatible jobs occupations.

Occupational Composition

Figure 8 illustrates shares of employment in major occupation groups across high and low teleworkable districts. I first classify the 3-digit occupation groups into twelve broad groups: Management, Business, and Financial; Computer, Engineering, and Science; Education, Legal, Community Service, Arts, and Media; Healthcare Practitioners and Technical; Service; Sales and Related; Office and Administrative Support; Farming, Fishing, and Forestry; Construction and Extraction; Installation, Maintenance, and Repair; Production; and Transportation and Material Moving.

In the upper panel, I compare the occupation distributions of men and women across low- and high-telework districts. In low-telework districts, women are heavily concentrated in agricultural farming (55.9%), alongside a 17.9% share in service occupations (17.9%). By contrast, men are spread more broadly across the spectrum: while they have a large share in farming (40.8%), they also hold substantial shares in non-teleworkable groups such as construction (13.5%), production (6.8%), and transportation (6.0%). They account for only 5.8% in high-teleworkability groups like management and finance. In the right upper panel, I show the distribution in high-telework districts. In these districts, the agricultural share drops dramatically for both women (to 35.0%) and men (to 21.6%) and more workers are absorbed primarily into service and production roles. Because this pattern of sectoral shifts mirrors closely between genders, it reflects that the identification strategy is designed to purge, instead of a gender-specific telework response. This is later empirically tested in section 5.

In the bottom panels, I compare occupation distribution between college-educated and less-than-high-school women. It reveals that telework exposure maps sharply onto education. In low-telework districts, college-educated women are highly concentrated in white-collar fields, particularly education and related professions (29.3%), service (25.7%), and office support (6.5%). Women with less than a secondary education, by contrast, are overwhelmingly employed in farming (61.7%) and service (17.6%), where telework is physically impossible. The distributions in high-telework districts confirm that the teleworkable margin varies exclusively for educated women. Across the district split, college-educated women reallocate sharply into the most teleworkable white-collar fields: management, business, and finance rises from 4.5% to 11.5%, computer, engineering, and science jumps from 2.6% to 8.2%, and office support grows to 9.7%, while traditional destinations like education fall to 21.2%. For less-educated women, employment in these remote-friendly jobs is almost non-existent in both types of districts. In highly teleworkable districts, less-educated women simply shift from farming into standard service and factory work.

Table 3. Top 10 and bottom 10 teleworkable occupations

NCO-2015 Code	Occupation	Probability Score	Above 0.468 (0/1)
Panel A: Top 10 most teleworkable occupations			
2310.0100	University and College Teacher—Arts Subjects	0.752936	1
2512.0203	Design Engineer (Product Engineer)	0.749795	1
2431.0502	Management Trainee—Sales and Marketing/Business Development	0.730513	1
2144.0803	Product Design Engineer	0.728672	1
2310.0200	University and College Teacher—Commerce Subjects	0.721268	1
2144.0801	Product Design Engineer	0.718926	1
2431.0501	Market Research Associate—Sales and Marketing/Business Development	0.715510	1
1221.0100	Sales Manager (Wholesale Trade)	0.715289	1
2310.0400	University and College Teacher—Education	0.712635	1
2431.0504	Management Trainee—Product Marketing	0.709785	1
Panel B: Bottom 10 least teleworkable occupations			
8160.8400	Filler, Aerated Water, Hand Machine	0.184522	0
7223.2900	Profiling Machine Operator	0.190846	0
8156.9900	Cutting, Lasting and Sewing Machine Operators, Other	0.191501	0
7126.0400	Straightening Machine Operator	0.194145	0
8219.0200	Assembler, Sewing Machine	0.194305	0
7223.2700	Dividing Machine Operator	0.195059	0
8156.0400	Heel Builder, Machine (Footwear)/Machine Operator—Heel Building	0.195432	0
8160.1200	Oil Crusher Operator, Power	0.196743	0
8142.1300	Mould Setter (Plastic)	0.197480	0
7223.1900	Rifling Machine Operator	0.199212	0

Notes: This table reports the ten most and least teleworkable occupations in the training set. The $\Pr(TW)$ in the third column is the predicted probability that an occupation is teleworkable using the NLP approach (eq. 17). The last column equals one if $\Pr(TW)$ exceeds the threshold of 0.468 and zero otherwise.

Digital Infrastructure

The second component of telework exposure is digital infrastructure. I measure district-level digital connectivity using the cell tower density which is defined as the number of cell towers per square kilometer of district land area. Cell towers capture availability of wireless broadband signal strength. Modern 4G and 5G towers depend largely on fiber-optic backhaul infrastructure. The National Digital Communications Policy of India (2018) enabled fiberizing at least 60% of telecom towers to accelerate 4G and 5G internet. Tower density is log-transformed to account for diminishing marginal returns to additional towers in already well-connected districts:

$$\text{Tower}_{dt} = \ln\left(1 + \frac{\text{Towers}_{dt}}{\text{Area}_d}\right) \tag{19}$$

where Towers_{dt} is the count of active mobile towers in district d in period t and Area_d is district area in square kilometers. I lag tower density by one year ($\text{Tower}_{d,t-1}$) to address reverse causality concerns. Because current activities can increase demand for telecom infrastructure, I lag the tower density by one year to reduce reverse causality concerns.

Telework Exposure Index

I define telework exposure index as function of occupational telework potential and digital infrastructure of each district. I combine these two components as following:

$$Exposure_{dt} = \left[TWO_d^{2007\text{–}12} \times \ln(1 + \text{Tower}_{d,t-1})\right] \tag{20}$$

where Exposure_{dt} is standardized to have zero mean and one standard deviation. The idea is that neither component alone is sufficient: (a) presence of teleworkable occupations is insufficient for a district's exposure if internet connectivity is highly uneven; (b) better internet access has no direct effect on flexible work arrangement if existing occupation structure is telework incompatible.

5 Empirical Strategy

I exploit within-district variation in telework exposure to identify their effect on women's labor supply. This approach builds on established research examining effects of local exposure on labor market outcomes (Acemoglu and Restrepo 2020; Hjort and Poulsen 2019b). The empirical strategy leverages temporal within-district variation in telework exposure while accounting for time-invariant district characteristics and time-varying year fixed effects.

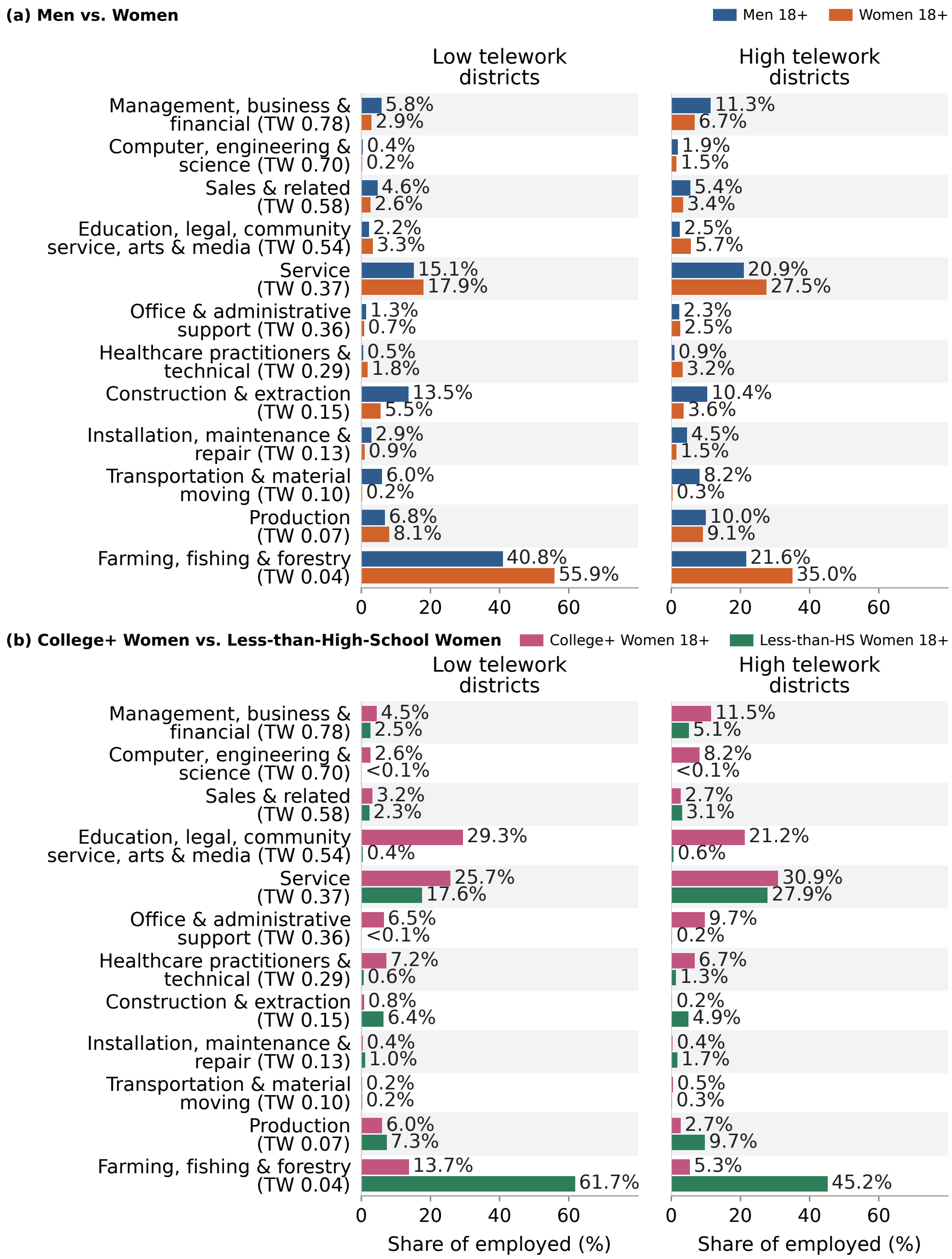


Figure 8. Occupation Distribution by Gender and Education. Upper panel compares overall employed men and women while the lower panel focuses only college-educated adult individuals. Districts are classified into high and low telework based on median value of district-level of telework-compatible occupation shares. Numbers in parentheses show occupation-level telework scores. Higher the value, higher is the telework-compatibility.

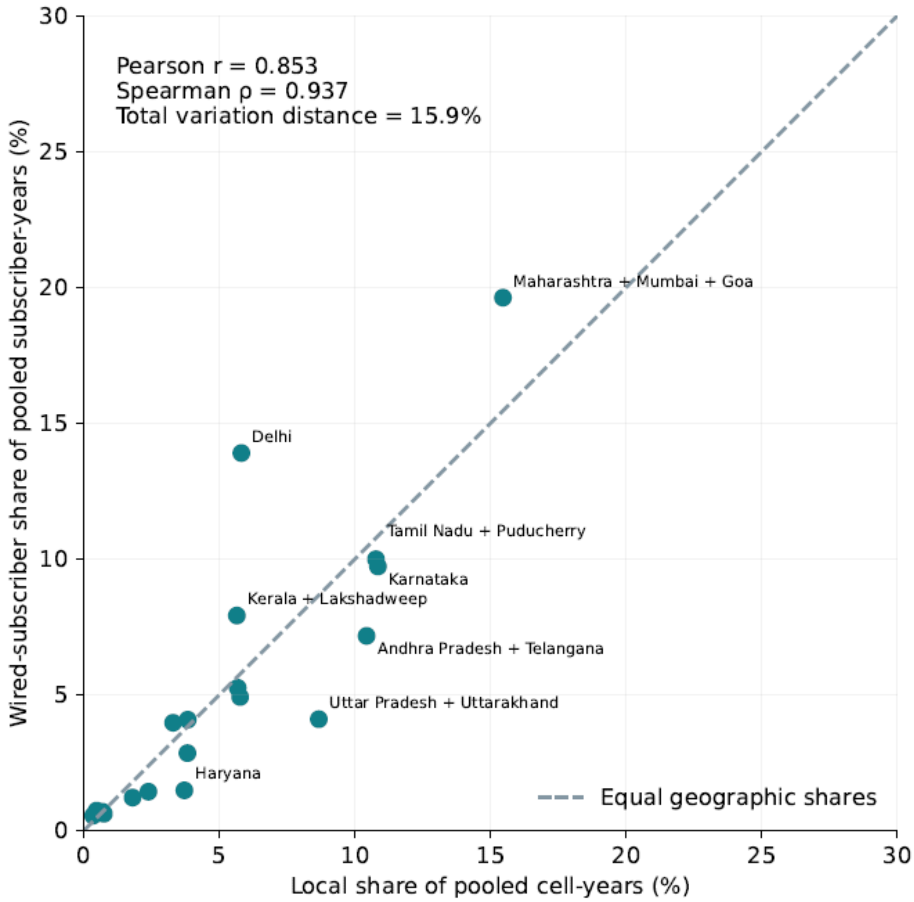


Figure 9. Relationship between TRAI wired broadband internet subscription and OpenCellID cell tower in India.

5.1 Baseline Specification

I utilize a two-way fixed effects (TWFE) model in the baseline specification to estimate the relationship between telework exposure and a woman's paid labor force participation using :

$$Y_{idt} = \alpha + \beta \cdot \text{Exposure}_{dt} + X'_{it}\gamma + \mu N_{dt-1} + \delta_t + \delta_d + \lambda_{st} + \varepsilon_{idt} \tag{21}$$

where Y_{idt} is a dummy if woman-i participates in labor market during year-t. Exposure_{dt} represents telework exposure of district-d in year t. X'_{it} is vector of individual characteristics of woman-i surveyed in year-t which include age, education level, marital status, religion, and social group. These covariates are significant determinants of women's labor supply. In India, education shares U-shaped relationship with women's participation (Klasen and Pieters 2015; Afridi, Dinkelman, and Mahajan 2017). That is, women's labor force participation is highest when they are either deprived of formal education or with college degrees. But women with middle or secondary education does not participate in labor market due to social stigma and lack of matching jobs. Age accounts for life-cycle differences in employment (Mincer 1974). Marital status influences domestic work, care-giving responsibilities, and social constraints around women's paid work(Afridi, Mahajan, and Sangwan 2022; Deshpande and Kabeer 2024; Park and Simpson 2026). Religion and social group captures heterogeneity in gender norms, access to education, discrimination and social network–all of which influence a woman's decision and resources to participate in paid labor (Sarkar, Sahoo, and Klasen 2019; Eswaran, Ramaswami, and Wadhwa 2013).

A potential concern is that changes in cell tower density which are incorporated into my telework exposure measure, can be correlated with a district's development trends which can influence female labor supply. For instance, districts that attract more public or private investment may receive more telecom infrastructure. To address this, I include lagged log of nighttime luminosity (N_{dt-1}). Martínez (2022)) utilize nighttime lights data to audit manipulation of official GDP figures. Several studies have used nighttime lights to capture local economic growth and time-varying development trends (Henderson, Storeygard, and Weil 2012; Michalopoulos and Papaioannou 2016; Gibson, Olivia, and Boe-Gibson 2020; Alesina, Michalopoulos, and Papaioannou 2016). The lagged values also matches with timing of cell tower information used in constructing telework exposure (Exposure_{dt}) for each district.This helps to isolate effects of telework exposure from confounding development trends.

I also account for time-varying state fixed effects (λ_{st}) because many Indian states have introduced cash transfer programs targeted at women which can impact household income and influence women's decisions to participate in paid labor.[11] λ_{st} absorb all time-varying state-level shocks.

Identification and Threats to Validity

The identifying assumption of equation (21) can be expressed as:

$$\text{Cov}\left(\text{Exposure}_{dt},\, \varepsilon_{idt} \,\middle|\, X'_{it},\, N_{dt-1},\, \delta_t,\, \delta_d,\, \lambda_{st}\right) = 0 \tag{22}$$

It states that the telework exposure is uncorrelated with error term after conditioning on residents' characteristics, development trends (captured by log of lagged nightlights data),

11. Assam's *Orunodoi scheme* in 2020, West Bengal's *Lakshmir Bhandar* in 2021, and a larger wave of schemes in 2023–2024 such as Madhya Pradesh's *Ladli Behna*, Karnataka's *Gruha Lakshmi*, Tamil Nadu's *Magalir Urimai Thogai*, Maharashtra's *Majhi Ladki Bahin*, Chhattisgarh's *Mahtari Vandan*, and Himachal Pradesh's *Pyari Behna scheme*

unobserved district, year and time-varying state fixed effects.

The key concern is that expansion of telecommunication infrastructure is not randomly assigned across districts. Mobile network operators are more likely to deploy additional towers where demand for telecommunications are highest. Districts with more educated population or experiencing faster urbanization can attract more investment in telecommunications and have higher female labor force participation. In such cases, changes in tower density may capture economic development instead of digital connectivity. This concern is particularly relevant because telework exposure is constructed as the interaction between district-level telework potential and local cellular infrastructure. Districts with higher baseline telework potential are also more likely to possess characteristics favorable to modern service-sector growth. Consequently, omitted changes in local economic conditions may generate a positive correlation between telework exposure and women's labor supply even after controlling for observed characteristics.

The empirical specification addresses these concerns in several ways. First, district fixed effects absorb all time-invariant differences across districts, including geography, historical industrial composition, social norms, and long-run development. Second, year fixed effects absorb nationwide macroeconomic shocks which can change over years. Third, state-by-year fixed effects capture time-varying state-level policies, such as female-targeted cash transfer schemes, labor-market interventions, and other state-specific economic shocks. Finally, lagged nighttime luminosity and interactions between baseline district characteristics and telecommunications expansion control for differential development trajectories across districts. However, these controls may not fully eliminate endogeneity if unobserved time-variant district-level characteristics simultaneously influence telecommunications investment and women's labor supply. A tower company, for example, Indus Towers, can have information about decisions on future economic activities that is not fully captured by lagged nighttime lights or time-invariant district characteristics. In this case, tower density and hence, telework exposure can be correlated with error term.

5.2 An Instrumental Variable Approach

To isolate exogenous variation in telecommunications infrastructure, I exploit differences in wireless signal strength across districts. Radio signals do not travel uniformly across space. Even when two locations are equally distant from a transmitter, geographic features such as hills, ridges, and valleys can strengthen or weaken signal reception. This terrain-driven variation helps address the endogenous placement of transmitters, which may otherwise be located to serve denser, wealthier, or politically important populations.

A growing economics literature uses the Longley–Rice Irregular Terrain Model (ITM) to separate variation in signal strength caused by geography from variation arising from transmitter placement. The Longley–Rice model combines transmitter characteristics with detailed elevation data to predict how terrain affects signal propagation. Studies have applied this approach to examine the effects of television and radio exposure on social capital (Olken 2009), political persuasion (Enikolopov, Petrova, and Zhuravskaya 2011), conflict (Yanagizawa-Drott 2014; Armand, Atwell, and Gomes 2020), political preferences (Adena et al. 2015; Durante, Pinotti, and Tesei 2019), and the electoral value of television celebrity (Xiong 2021). These studies predict signal strength from observed broadcasting transmitters because their objective is to estimate the effects of access to an existing communication network.

In this paper, the endogeneity in telework exposure is arising due to cell tower placement. If I use observed cellular transmitters to calculate predicted signal strength, this would give rise to the same endogeneity issue because locations of transmitter are chosen by mobile network operators based on local demand or economic activities. Instead of reproducing India's actual cellular network, I evaluate how radio signals would travel if every district were served by the same hypothetical set of transmitters. This is called common reference transmitter network. Specifically, I place identical hypothetical transmitters on a regular lattice across the Indian land area.[12] This is shown in figure 14. Then, I utilize the Irregular Terrain Model (ITM) alongside terrain tiles to predict the received signal strength at specific receiver locations in each district.[13] The resultant map is shown in figure 10. For each district-d, I construct predicted radio signal strength, A_d^{ITM} and instrument telework exposure, $Exposure_{dt}$ with:

$$Z_{dt} = TWO_d^{2007-12} \times A_d^{ITM} \times 4G_t \tag{23}$$

12. To simulate the network, I construct a standardized grid of hypothetical transmitters and receivers across India. I place simulated transmitters every 50 kilometers and receivers every 20 kilometers to ensure complete geographic coverage across all districts. This grid is dense enough that all 8,403 receiver locations have multiple nearby transmitters and there is no coverage gaps. Note that electrical engineers often predict signal coverage from planned or hypothetical transmitter locations before physical networks are deployed (Yapar 2026; Mlinar, Podgrajšek, and Batagelj 2023; Stine 2009).

13. Using the Longley–Rice model, the receiver connects only to the single strongest signal. This mirrors how real-world mobile phones automatically link to the best available cell tower. To calculate a final score for an entire district, I average the strongest signal strengths recorded across all receivers in that area.

The instrumental variable combines two sources of variation. First, it captures geographical differences in how easily wireless signals travel across districts. Second, the nationwide roll out of cheap 4G expansion during late 2016 triggered uniform shock, which made these geographic advantages much more valuable. As a result, districts with both a natural geographic advantage and a higher baseline potential for remote work saw the largest predicted gains in telecommunications infrastructure when 4G expanded. One concern could be that predicted signal strength (A_d^{ITM}) depends not only on terrain but also on distance from the hypothetical transmitters. Some districts may be closer to the hypothetical transmitters than others, even in absence of terrain. This, in turn, can influence differential gains from 4G expansion. I address this by accounting for free-space signal strength in Equation (24) as control variable.[14] Hence, the identification is driven by the remaining variation which is terrain-driven signal strength.
The first-stage relationship is:

$$\text{Exposure}_{dt} = \pi_0 + \pi_1 Z_{dt} + \pi_2 \left(A_d^{FSS} \times 4G_t \right) + N_{dt-1}\mu + \delta_d + \delta_t + \lambda_{st} + \nu_{idt}, \tag{24}$$

and the second stage specification is as following:

$$Y_{idt} = \beta_0 + \beta_1 \hat{\text{Exposure}}_{dt} + X'_{it}\beta_2 + \mu N_{dt-1} + \theta_t + \theta_d + \theta_{st} + \epsilon_{idt} \tag{25}$$

where, $\hat{\text{Exposure}}_{dt}$ is predicted telework exposure from the first stage and β_1 is main coefficient of interest. π_1 captures whether districts with greater baseline telework potential and more favorable signal quality experienced larger increases in telework exposure as 4G expanded countrywide. A positive and statistically significant estimate of π_1 indicates that the instrument is strongly associated with the endogenous measure of telework exposure.A_d^{FSS} is free-space signal strength and ($A_d^{FSS} \times 4G_t$) measures district-d's gains from 4G expansion based on their free-space signal strength.

14. Free-space signal refers to the expected signal level in absence of any barriers such as no terrain.

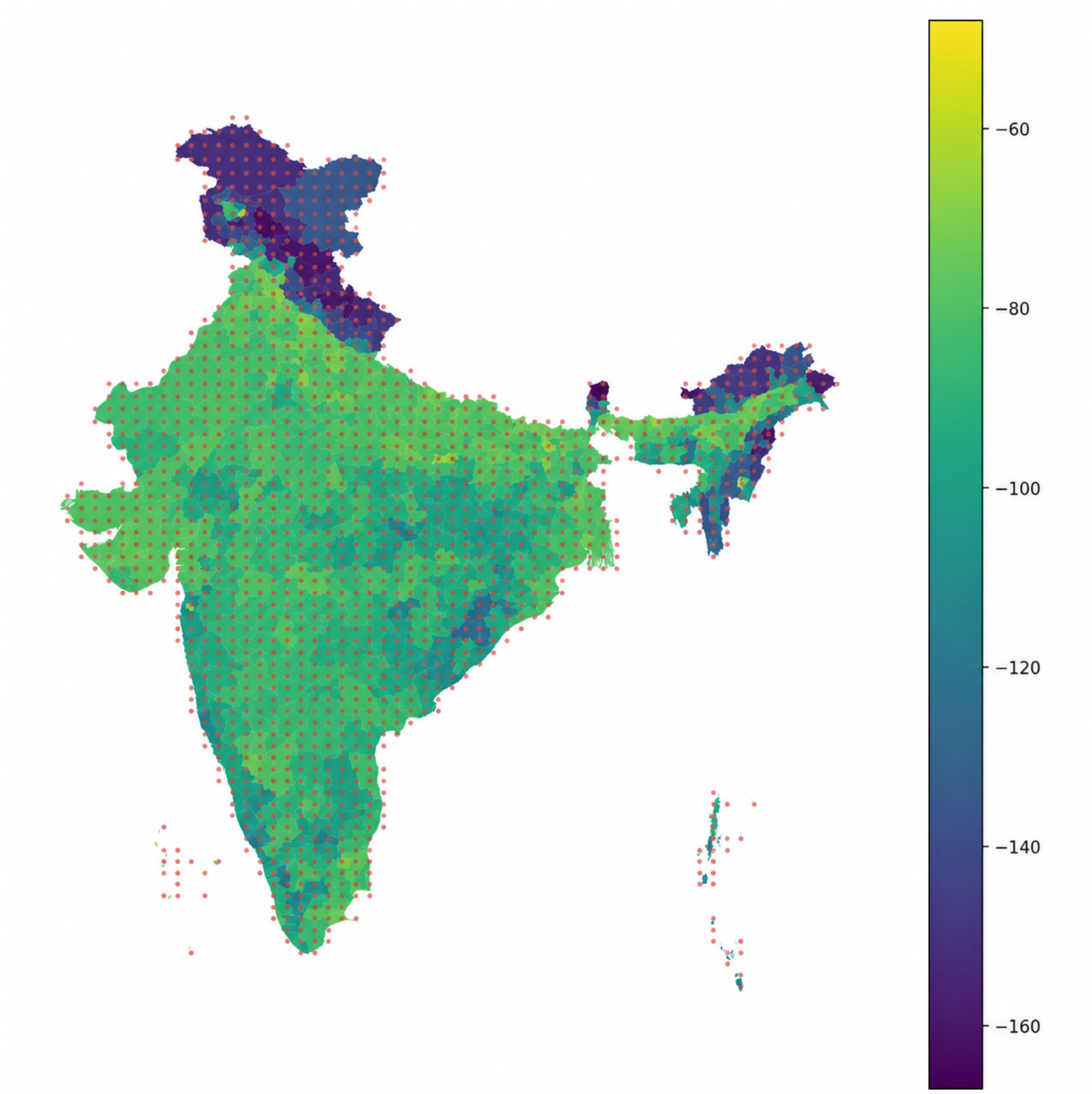


Figure 10. Hypothetical transmitter lattice used to evaluate district-level propagation suitability. Identical transmitters are placed on a fixed 50 km grid in projected space and clipped to India's land area. Because placement depends only on geography and not on realized telecommunications infrastructure or economic activity, all districts are evaluated under common transmission conditions.

6 Results

6.1 Key Results

Table 4 presents the effects of telework exposure on the labor market outcomes by gender. Columns (1) and (3) report the OLS estimates for overall participation in the labor market, while columns (2) and (4) report the results for 2SLS estimates by gender.

Baseline Results. A one-standard-deviation increase in telework exposure raises the likelihood of being in the labor force by 2.77 percentage points (pp) (Column 1, Table 4). But the effect is insignificant in case of men (Column (3), Table 4). The magnitude of the OLS estimates for women's labor market outcomes are economically significant. Since the average participation of 28.7%, the estimated effect represents nearly 10% of the mean labor supply. These results suggest that districts with higher exposure to telework potential experience higher female labor force participation. I also show this relationship graphically in figure 12 using both continuous and binned telework exposure. Panel (3a) confirms positive and monotonically increasing relationship. Panel (3b) corroborates similar pattern without imposing linearity.

IV Results. In Table 4, column (2) shows the 2SLS estimate which implies that a 1 SD increase in telework exposure makes women 8.46 pp more likely to participate in paid labor. This is further confirmed by Anderson–Rubin p value in Table 4. The 2SLS estimate amounts to 8.3% women's participation which is 23% of overall FLFP. Moreover, the effect of $A_d^{FSS} \times 4G_t$ is statistically insignificant which is consistent that the identifying variation is coming from the ITM component instead of free-space signal strengths. Men's participation is marginally responsive to telework exposure (Column 4, Table 4). The first stage results are strong and shown in column 1 in Tables 13 and 14 of Appendix C.3.[15]

The above estimated coefficients contributes to the growing literature on female labor supply responses to remote work and flexible work arrangements. In advanced economies, the estimated effects of remote work expansion on women's labor force participation is smaller than that of the developing countries. For example, Song (2026) finds that a one-standard-deviation increase in remote work potential raises participation of college-educated mothers in full-time employment by 0.65 pp. Similarly, Harrington and M. E.

15. It is important to note that the presence of $TWO_d^{2007-12}$ on both sides of the first-stage equation 24 can mechanically lead to a strong first stage correlation between endogenous regressor and instrumental variable. But this does not itself invalidate the 2SLS estimates which are reported in columns (2) and (3) as long as the exclusion restriction is satisfied: conditional on demographic controls and fixed effects, Z_{dt} affects women's labor supply on through Exposure_{dt}. That is,

$$\text{Cov}(Z_{dt}, \varepsilon_{dt} \mid X_{idt}, \delta_d, \delta_t, \lambda_{st}) = 0.$$

While the common $TWO_d^{2007-12}$ can contribute to instrumental relevance condition, the 2SLS estimate remains unbiased as long as the instrumental variable is orthogonal to unobserved determinants of female labor supply. Nevertheless, I use another instrumental variable in robustness check where I use predetermined shares of teleworkable industries instead of $TWO_d^{2007-12}$ in Z_{dt}.

Kahn (2026) shows that a 10% increase in work-from-home raises mother's employment by 0.94% relative to others. Amuedo-Dorantes et al. (2023) shows that the COVID-19 induced school closures reduced mother's employment by 8.1 pp less in teleworkable occupations than for non-teleworkable occupations. The magnitude is relatively higher in emerging economies. For instance, Zarate (2025) shows that remote work reduces the child penalty by 4 pp. While not directly measuring remote work, Berniell et al. (2023) shows that working women increase their participation in flexible employment by 16-50% after childbirth. In India, the two RCTs show that home-based job opportunities increase women's participation by 29 pp. Compared to these studies, the estimated effects is moderate (2.77 pp) in case of OLS approach while the IV estimate (8.46 pp) is high but within the range of responses where flexible work arrangements relax binding constraints.

The IV estimated coefficient is much larger than the OLS estimate (Column 1, Table 4). This could be attributable to three reasons. Firstly, the OLS estimate could be biased downward due to omitted variable bias. Cell towers are mainly built in areas characterized by urbanization, and economic growth. Goldin (1995) showed that there is a U-shaped relationship between female labor supply and development. In India, female labor force participation declined with urbanization because such structural transformation preferred sectors which least favored female workers (Klasen and Pieters 2015; Klasen 2019; Jayachandran 2020). Since it is not possible to isolate the true effects of telework exposure from other time-varying district-level characteristics, OLS estimate could underestimate the true effect.

Secondly, classical measurement error could attenuate OLS estimates toward zero. The baseline telework exposure is interaction between share of telework-compatible jobs and lagged cell tower density. But data on cell tower counts are noisy and more likely to undercount in areas where lesser devices contribute pings. Instead of relying on crowdsourced information, the IV captures district's digital connectivity through its radio propagation and hence strips out any possible noise from cell tower density measure. Lastly, the IV identifies local average treatment effect (LATE) of telework exposure on women whose local signal strength determines gains in digital connectivity from nationwide 4G rollout. Thus, the LATE is most relevant in districts where gains from 4G expansion are likely to have largest effect on women due to limited alternative options. These include districts with rugged terrains, crime rates, assuming similar distributions of telework-compatible occupations.

Table 4. Telework Exposure and Paid Labor Supply by Gender

	Women		Men	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Telework exposure	0.0277***	0.0846***	0.0052	0.0093*
	(0.0061)	(0.0138)	(0.0035)	(0.0053)
Individual controls	Yes	Yes	Yes	Yes
Lagged nighttime lights	Yes	Yes	Yes	Yes
FSS signal × 4G growth	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
State × year fixed effects	Yes	Yes	Yes	Yes
Survey weights	Yes	Yes	Yes	Yes
Kleibergen–Paap rk Wald F	–	106.27	–	103.02
Kleibergen–Paap rk LM p-value	–	< 0.001	–	< 0.001
Observations	579,340	579,340	569,554	569,554

Notes: The table reports OLS and 2SLS estimates of the effect of telework exposure on paid labor supply of women and men over age 18 years. Columns (1) and (2) report estimates for women, while Columns (3) and (4) report estimates for men. All specifications include controls for age, education, marital status, religion, and social group; lagged nighttime lights; district fixed effects; year fixed effects; and state-by-year fixed effects. PLFS sampling weights are used in all specifications. Standard errors, clustered at the district level, are reported in parentheses. The Kleibergen–Paap statistics are reported for the 2SLS specifications. This table shows that women's participation is more responsive to telework exposure than men. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Full Regression tables are in Appendix C.3.

6.2 Heterogeneous Effects

Table 5 examines whether the effect of telework exposure varies with marital norms (Panel A), household socioeconomic conditions (Panel B) and education levels over different stages of life cycle (Panel C). Understanding such variations is useful to identify who gets more benefited from higher telework potentials and inform targeted policy interventions. Moreover, heterogeneous effects help to examine whether telework exposure reduces cost of paid work. If a district's high telework potential relaxes social norms, the effects should be stronger among subgroups for whom social constraints are binding.

Norms around marriage and responsibilities. Panel A examines whether women with marriage-related constraints are more responsive to telework exposure. First, I compare women who are currently married with those who are unmarried (Column 1, Panel (A)). In next two columns, I only focus on currently married women to capture constraints within household. I compare whether the effect of telework exposure varies with the presence of at least one child aged 9 years or less in a household (Column 2, Panel (B)). Finally, I assess whether co-residence with extended family affect the relationship between telework exposure and female labor supply (Column 3, Panel (C)). This is especially relevant in South Asia where patrilocal living arrangements remain important.

In response to one-standard-deviation increase in telework exposure, married women are 8.62 percentage points more likely to participate in paid labor than never-married women (Column 1, Panel (A)). In fact, the effect of telework exposure among never-married women is statistically insignificant (Column 1, Panel (A)). This accounts for nearly one-third of the mean female labor force participation. The presence of at least one child aged 0-9 years further increases the effect of telework exposure on married women's labor supply by 2.13 percentage points compared to those without children aged 0-9 years. Household structure also matters for married women with young children. For women in patrilocal households, the effect of telework exposure is 10.3 percentage points. A one-standard-deviation increase in telework exposure further raises married women's labor supply by 2.14 percentage points in nuclear households compared to patrilocal households. This suggests that women with young children are more responsive to telework exposure when they live in nuclear households than in patrilocal households.

Socioeconomic conditions of households. Panel B shows how the relationship between telework exposure and female labor supply by household-level economic and social characteristics. Previous studies have shown that women's participation is often high to alleviate financial distress in poor households, while paid work tend to rise among women in more affluent families with access to better quality jobs (Klasen and Pieters 2015; Sarkar, Sahoo, and Klasen 2019; Deshpande and Kabeer 2024). I measure household economic status by monthly per capita consumption spending. This choice is driven by permanent income hypothesis which suggests that current consumption more directly measures material well-being than current income (Meyer and Sullivan 2003; Carver and Grimes 2019; Deaton 2016). I classify households into high- and low-economic-status groups based on whether their monthly per capita consumption expenditure (MPCE) is above or below the sample median. For a one-standard-deviation increase in telework exposure, women are

2.3 percentage points more likely to supply paid labor if they belong to households with above-median MPCE than those below it (Column 1, Panel (B)).

Moreover, social group plays an important role. Scheduled Castes and Scheduled Tribes (SC/ST) are historically disadvantaged social groups that are eligible for reservations in public education and employment. In panel (B), column (3) compares households which are traditionally advantageous vs SC/ST. I show that the effect of telework exposure is 5.56 percentage points less among women in the socially minority group than women from advantageous households (Column 2, Panel (B)). This suggests that improvements in digital connectivity and access to telework-compatible occupations do not translate uniformly into employment gains across the social hierarchy. Women from historically disadvantaged groups may face additional barriers. Lastly, column (3) shows that the heterogeneous effects of gender of household headship is modest. A one-standard-deviation increase in telework exposure raises female labor supply by 1.9 percentage points more in female-headed households compared to male-headed households (Column 3, Panel (B)).

Human Capital over Life Cycle. Panel C examines how the effects of telework exposure on female labor supply vary by higher education across different stages of life cycle. I focus on different age groups because the marginal value of flexible work arrangements differs across different age groups, especially among women with advanced education levels. Here, I restrict the sample to women with formal schooling and exclude those whose education is limited to non-school literacy initiatives. In columns (1)-(3), I compare the relationship between telework exposure and female labor supply between college-educated women and those with less than college-level education (that is, diploma, high-school education or less) across various age groups. I focus on women aged 24-44 years since individuals typically complete bachelor's and master's degrees by 23 years while most women aged above 44 years have older children and face less social constraints than younger married women.

Panel C shows two patterns. First, the effect of telework exposure is consistently positive and significant on women with less than college-level education across all age groups. This suggests that the effect of telework exposure on less-educated women's paid labor does not depend on their career stage, as expected. Second, the effect of college-premium varies non-linearly over the life cycle. In early career stages (during 24-29 years), women with college degrees are less responsive to telework exposure compared to less-educated women (Column 1, Panel (C)).

Table 5. Heterogeneous Effects of Telework Exposure on Women's Paid Labor

Panel A. Norms around marriage and family responsibilities	Married (1)	Young child (2)	Household structure (3)
Exposure_{dt}	0.0186	0.0870***	0.1030***
	(0.0335)	(0.0159)	(0.0195)
$\text{Exposure}_{dt} \times$ Currently married	0.0862**		
	(0.0372)		
$\text{Exposure}_{dt} \times$ Child aged 0–9		0.0213**	
		(0.0101)	
$\text{Exposure}_{dt} \times$ Nuclear household			0.0214**
			(0.0097)
Observations	494,623	427,007	341,063

Panel B. Household socioeconomic conditions	Household resources (1)	Social group (2)	Household head (3)
Exposure_{dt}	0.0646***	0.0946***	0.0790***
	(0.0159)	(0.0139)	(0.0135)
$\text{Exposure}_{dt} \times$ High MPCE	0.0230***		
	(0.0083)		
$\text{Exposure}_{dt} \times$ Disadvantaged social group		−0.0599***	
		(0.0153)	
$\text{Exposure}_{dt} \times$ Female-headed household			0.0191**
			(0.0087)
Observations	579,340	579,340	579,340

Panel C. Human capital over the life cycle	24–29 (1)	30–34 (2)	35–39 (3)	40–44 (4)
Exposure_{dt}	0.0855***	0.1020***	0.1084***	0.0750***
	(0.0251)	(0.0252)	(0.0254)	(0.0263)
$\text{Exposure}_{dt} \times$ College+	−0.1040***	−0.0337	0.0739**	0.0073
	(0.0325)	(0.0287)	(0.0353)	(0.0286)
Observations	76,488	54,209	54,058	41,842

Notes: All specifications are estimated by 2SLS and include the baseline individual controls, lagged nighttime lights, district fixed effects, year fixed effects, state-by-year fixed effects, and PLFS sampling weights. Standard errors, clustered at the district level, are reported in parentheses. In panel A, column (1) compares currently married with never-married women; columns (2) and (3) are restricted to married women to compare women with children aged 0–9 years and household structure, respectively. Panel B examines heterogeneity by household resources, social group, and gender of the household head. Panel C compares college-educated and less-educated women across four age groups. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

This negative effect declines and becomes insignificant among women in early thirties (Column 2, Panel (C)). The effects become positive and statistically significant among women aged 35-39 years. For every one-standard-deviation increase in telework exposure, paid labor supply rises by 7.4 percentage points more among college-educated women in late thirties than those with less than college-level education (Column 3, Panel (C)). In twenties, early-stage professionals have higher returns to in-person networking, mentoring in white-collar jobs (Atkin, Schoar, and Shinde 2023; Jensen 2012). This reduces the marginal value from flexible work arrangements among young college-educated women compared to those with high school education or less. By their late thirties, women have accumulated more labor-market experience, while childcare and family responsibilities often remain substantial. This increases demand for telework arrangements among higher educated women in their late thirties for maintaining their jobs.

6.3 Robustness Checks

6.3.1 Alternative Instrumental Variable.

One concern with the existing instrument is that it mechanically drives the first stage relationship. So, I proxy district-level shares of predetermined teleworkable occupations with that of teleworkable industries to define an alternative instrument:

$$W_{dt} = TWIND_{dt}^{2007-12} \times A_d^{ITM} \times 4G_t \tag{26}$$

In table 6, column (1) shows that the industry-based instrument strongly correlates with the endogenous regressor and the F-statistic indicates a strong instrument. Column (2) reports the 2SLS estimated coefficient which is consistent with the main results.

6.3.2 Sensitivity to Instrument Construction

Network Resolution. The construction of predicted signal strength in the IV design requires placing hypothetical transmitter and receiver grids. In the main specification, I place transmitters 50 km apart and receivers 20 km apart to ensure multiple nearby transmitters for each receiver while covering geographic areas across all districts. To examine whether the estimated coefficients depend on these choices, I reconstruct terrain-adjusted ITM signal and free-space signal strength by placing transmitter and receiver

Table 6. Alternative Industry-Based Instrument

	(1) First stage	(2) 2SLS
Dependent variable:	Telework exposure	Paid labor
$INDTW_d \times A_d^{ITM} \times 4G_t$	1.101***	
	(0.160)	
Exposure_{dt}		0.0876***
		(0.0183)
Individual controls	Yes	Yes
Lagged nighttime lights	Yes	Yes
FSS signal × 4G growth	Yes	Yes
District fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
State × year fixed effects	Yes	Yes
Survey weights	Yes	Yes
Kleibergen–Paap rk Wald F	47.49	
Kleibergen–Paap LM p-value	< 0.001	
Anderson–Rubin p-value		< 0.001
Observations	579,340	579,340

Notes: This table reports first stage and 2SLS estimates using alternative instrumental variable. $TWIND_d$ denotes district-level shares of telework-compatible constructed from NIC-2008 industry classification. All specifications control for individual characteristics, lagged nighttime lights, district fixed effects, year fixed effects, and state × year fixed effects. PLFS survey weights are used throughout. Standard errors, shown in parentheses, are clustered by district. The model is exactly identified. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

grids that are 20% coarser[16] and 20% finer[17] than those used in main specification (4). In Appendix C.4.1, Table 15 show the results where columns (1) and (3)report estimates for coarser and finer networks while column (2) indicates results for the baseline specification from Table 4. The estimated coefficients are consistent across all these specifications.

16. That is, transmitters are placed 60 km apart and receivers 24 km apart. This network contains 876 hypothetical transmitters and 6,063 receiver locations

17. That is, transmitters are placed in every 40 km and receivers 16 km apart. This network consists of 1,957 transmitters and 12,864 receivers

Alternative Networks. Next, I examine whether the estimates are robust to alternative choices of placement of transmitter, receiver and changing the grid origin. Firstly, I alter receiver locations by holding transmitters fixed at every 50 km. Secondly, I vary transmitter locations while holding receivers fixed at every 20 km. Lastly, I shift the origin of transmitter grid. Across all these alternative specifications, the results range from 7.9 percentage points to 8.9 percentage points which remain consistent with the main results (Table 16, Appendix C.4.1). These indicate that the main estimated coefficient is robust to constructions of alternative hypothetical signal network.

6.3.3 Excluding COVID-19 pandemic years

Since the main sample covers data during 2017-2024, it is plausible that the effects can be influenced by the COVID-19 pandemic (2020-21). Though year fixed effects absorb the nationwide shock due to the pandemic, it is true that some districts were affected more than others and have different socioeconomic impacts. Densely populated and metropolitan districts (e.g., Mumbai, Chennai, Delhi) experienced the highest COVID-19 cases. This would confound the identifying variation instead of being absorbed by the year fixed effects. To evaluate whether the main estimates are driven by pandemic era, I estimate the main equation (25) by dropping observations during the pandemic years (2020-21). In Appendix C.4.3 Table 17 reports the results which show that the estimated coefficients are consistent with the main results (Column (2), Table 17).

6.3.4 Pre-existing Female Labor Trends

One concern is that districts with varying telework exposure have different trends in female labor supply (Harrington and M. Kahn 2025). For example, if districts with greater telework exposure were already on a rising FLFP trajectory, the effects of telework exposure could capture the lagged trends instead of the causal effects. To address this, I augment the 2SLS specification by controlling for lagged linear FLFP trends by districts. In Appendix C.4.4, column (1) of Table 18 confirms that the estimated coefficients are consistent with key results, though smaller in magnitude.

6.3.5 Additional Robustness Checks

District Representativeness. Another potential concern lies with the sampling design of the PLFS database. It is designed to be nationally representative. Following Peters et al. (2025), I restrict my sample only to those districts with at least 50 observations in each year which reduces the number of districts from 600 to 576. In Appendix C.4.4, column

(2) of Table 18 shows that the estimates remain robust and similar to the key results after excluding noisier district-year observations.

Restricting women of reproductive age. The main results include adult women aged above 18 years. As a robustness check, I restrict the sample to women aged 18–44 years when fertility and childcare responsibilities shape labor supply decisions. In Appendix C.4.4, column (3a) of Table 18 shows the estimated coefficient remains consistent with the main results.

Excluding older cohorts. Song (2026) argues that workers in late fifties are more likely to retire than their younger cohorts instead of retaining their employment through flexible work arrangements. In India, the retirement age is around 60 years. So, I restrict the sample to 19-59 years to address this concern. In Appendix C.4.4, column (3b) of Table 18 shows that the results remain stable and slightly larger in magnitude.

7 Cost Benefit Analysis

I use the preferred IV estimated coefficient on female employment to calculate benefits associated with expansion in telework exposure from the expansion of 4G infrastructure. Using back-of-the-envelope approach, I compare the annual earnings associated with the estimated increase in women's employment with the annual-equivalent cost of expanding 4G digital infrastructure. Following related cost benefit analyses in development economics literature (Duflo and Pande 2005; Vogel et al. 2024), the calculations are intended to evalueate an order-of-magnitude instead of a complete welfare evaluation. I evaluate the benefits of specific increase in telework exposure and compare those benefits with an official benchmark for the cost of expanding 4G infrastructure. The baseline calculation considers a 0.10-standard-deviation increase in telework exposure. The resulting benefit-cost ratio should be interpreted as a scenario-based comparison instead of causal effects of the government's 4G expansion program.

7.1 Method

Let s denotes the assumed change in standardized telework exposure. The preferred IV specification implies that a one-standard-deviation increase in telework exposure raises women's employment probability by 9.19 percentage points ($\hat{\beta} = 0.0919$, $SE = 0.0148$). Under the baseline scenario, $s = 0.10$, implying an increase in employment of

$$\Delta p = s\hat{\beta} = 0.10 \times 0.0919 = 0.00919, \tag{27}$$

or 0.919 percentage points.

For district d, I translate this employment effect into an annual earnings-equivalent benefit according to

$$B_d(s) = s\hat{\beta} \times N^F_{d,19-59} \times \bar{Y}^F_d, \tag{28}$$

where $N^F_{d,19-59}$ denotes the population of women ages 19–59 and $\bar{Y}^F_d$ denotes average annual earnings among employed women in district d. Earnings are measured using the district-level annual earnings measure constructed from the PLFS. Aggregating across districts gives

$$B^{IND}(s) = \sum_d B_d(s). \tag{29}$$

This approach values each additional employed woman with the average female earnings in a district.

Infrastructure costs. For the national cost benchmark, I use the Government of India's saturation project for 4G mobile services in uncovered villages. The approved project cost is INR 263.16 billion and includes both capital expenditure and five years of operating expenditure (Press Information Bureau, Government of India 2022). The initial implementation plan corresponds to 19,722 mobile towers (Press Information Bureau, Government of India 2023), implying a total project-cost benchmark of approximately INR 13.34 million per planned site. Because the reported project cost already includes five years of operating expenditure, I do not treat the entire amount as a pure capital expenditure with a ten-year asset life. Instead, I convert the total project outlay into a five-year equivalent annual cost. Let

$$A_5(r) = \sum_{\ell=1}^{5} \frac{1}{(1+r)^\ell} = \frac{1-(1+r)^{-5}}{r}. \tag{30}$$

Using a discount rate of $r = 0.05$, the annual-equivalent national cost is

$$C^{IND} = \frac{263.16 \text{ billion}}{A_5(0.05)} = 60.78 \text{ billion INR per year.} \tag{31}$$

This interprets the reported project outlay as a present-value resource cost distributed over the five-year operating horizon. For the district-level exercise, I use the geographic distribution of post-2017 additions in OpenCellID as a proxy for the spatial distribution of infrastructure expansion. Let q_d denote additional tower for district d. The annual-equivalent cost benchmark per tower is

$$\tilde{\kappa} = \frac{263.16 \text{ billion}/19{,}722}{A_5(0.05)} \simeq 3.08 \text{ million INR}, \tag{32}$$

and district-level cost is

$$C_d = q_d \tilde{\kappa}. \tag{33}$$

The net benefit and benefit-cost ratio are

$$W_d = B_d - C_d \tag{34}$$

and

$$BCR_d = \frac{B_d}{C_d}. \tag{35}$$

At the aggregate level, I report

$$BCR^{IND} = \frac{\sum_d B_d}{\sum_d C_d}, \tag{36}$$

rather than the average of district-specific benefit-cost ratios.

7.2 Results

Table 7 reports the India-wide baseline calculation. Census 2011 records approximately 587.6 million women and 60% of them belong to working-age 19–59 years. A 0.10-standard-deviation increase in telework exposure raises the predicted employment probability by 0.919 percentage points, implying approximately 3.24 million additional employed women. Using district-specific annual earnings, these employment gains correspond to approximately INR 366.65 billion in annual earnings-equivalent benefits. The corresponding weighted annual earnings of the marginal employment gains are approximately INR 113,166 per woman.

7.2.1 Sensitivity Analysis

The baseline results necessarily depend on the magnitude of the assumed change in telework exposure, and infrastructure costs. Table 8 therefore reports several alternative calculations. Panel A shows the employment effect over its 95 percent confidence interval while holding the exposure increase at 0.10 standard deviations. Using the lower confidence bound, the annual earnings-equivalent benefit is approximately INR 250.92 billion and the benefit-cost ratio remains above four. At the upper confidence bound, the corresponding benefit is INR 482.38 billion and the benefit-cost ratio rises to 7.94. Panel B varies the assumed exposure change. A smaller 0.05-standard-deviation increase generates approximately INR 183.33 billion in annual earnings-equivalent benefits and a benefit-cost ratio of 3.02. A 0.25-standard-deviation increase produces a substantially larger benefit, although these calculations should be interpreted as linear extrapolations of the estimated treatment effect. These calculations indicate that the estimated employment gains can be economically large relative to plausible infrastructure costs.

The annual-equivalent cost of the national 4G saturation project is approximately INR 60.78 billion. Under the baseline assumptions, the resulting annual net benefit is therefore approximately INR 305.87 billion, with an aggregate benefit-cost ratio of 6.03. Thus, under the 0.10-standard-deviation exposure scenario, each rupee of annual-equivalent infrastructure cost is associated with approximately INR 6.03 in annual earnings-equivalent benefits. Following Duflo and Pande (2005), I also consider a 15 percent deadweight-loss markup on publicly financed infrastructure costs. This increases annual-equivalent cost to approximately INR 69.90 billion, while annual net benefits remain approximately INR 296.75 billion. The corresponding benefit-cost ratio is 5.25.

Table 7. Baseline Cost-Benefit Analysis

	Value
A. Parameters and Population	
Estimated employment effect per 1 SD of telework exposure	0.0919
Standard error	0.0148
Baseline increase in telework exposure (SD)	0.10
Implied increase in employment probability	0.00919
Census 2011 female population	587,584,719
Assumed share of women ages 19–59	0.60
Female population ages 19–59	352,550,831
Weighted annual earnings per additional employed woman (Rs.)	113,166
B. Annual Earnings-Equivalent Benefits	
Additional employed women	3,239,942
Aggregate annual earnings-equivalent benefit (Rs.)	366,651,203,350
C. Infrastructure Cost	
Total cost of national 4G saturation project (Rs.)	263,160,000,000
Initially planned mobile towers	19,722
Implied total project cost per planned site (Rs.)	13,343,474
Annual-equivalent project cost, 5-year horizon (Rs.)	60,783,327,875
D. Baseline Cost-Benefit Results	
Aggregate annual net benefit (Rs.)	305,867,875,475
Aggregate benefit-cost ratio	6.032
Annual cost including 15% deadweight loss (Rs.)	69,900,827,057
Annual net benefit including 15% deadweight loss (Rs.)	296,750,376,293
Benefit-cost ratio including 15% deadweight loss	5.245

Notes: The baseline calculation evaluates a 0.10-standard-deviation increase in standardized telework exposure. The employment effect is the preferred IV estimate for women ages 19–59. The working-age female population is approximated as 60 percent of Census 2011 female population. Benefits are annual earnings-equivalent gains and should not be interpreted as a complete measure of welfare. The INR 263.16 billion national 4G saturation project cost includes capital expenditure and five years of operating expenditure and is converted to a five-year equivalent annual cost using a 5 percent discount rate.

Table 8. Sensitivity Analysis Results

	Benefit	Cost	Net Benefit	BCR
		(Rs. billion)		
Panel A. IV Effect Sensitivity, 0.10-SD Exposure Increase				
Lower 95% bound (β = 0.0629)	250.92	60.78	190.14	4.128
Point estimate (β = 0.0919)	366.65	60.78	305.87	6.032
Upper 95% bound (β = 0.1209)	482.38	60.78	421.60	7.936
Panel B. Exposure-Scenario Sensitivity				
0.05 SD	183.33	60.78	122.54	3.016
0.10 SD	366.65	60.78	305.87	6.032
0.25 SD	916.63	60.78	855.84	15.080

Notes: Panels A and B report India-wide annual earnings-equivalent benefits. Panel A varies the preferred IV coefficient over its 95 percent confidence interval. Panel B varies the assumed increase in standardized telework exposure while holding the IV coefficient at 0.0919. All cost calculations use the preferred five-year annual-equivalent cost of the national 4G saturation project.

8 Conclusion

This paper examines whether female labor supply responds to telework exposure in the context of an emerging economy where social norms discourage women away from labor market. For every one-standard-deviation increase in telework exposure, women are 8.46 percentage points more likely to participate in the labor market. Who benefits, and who does not? The positive effects are concentrated among women who are married, have young children and belong to nuclear households. Besides, the gains are concentrated among women from upper caste and economically better-off households. College education plays an important role, especially for women in their late thirties. These patterns imply that telework exposure can relax social barriers to female labor supply in emerging economies, but the benefits depend on whether women have the household resources and skills necessary to take advantage of telework opportunities.

A key contribution of this paper is the construction of telework scores for each occupation. I develop this by applying supervised text classifier to the detailed occupation manual. This provides a country-specific alternative to telework measures derived from U.S. task surveys and similar data from advanced economies. The resulting scores can be merged with other datasets containing Indian occupation codes and used to study a broader set of questions, including time use, wage inequality, occupational mobility, and employment transitions. They can also be aggregated across industries, regions, or demographic groups, making them useful for researchers studying the Indian labor market. More broadly, the same framework can be applied in other emerging economies where detailed task surveys are unavailable but national occupational descriptions exist. This expands the set of countries in which exposure to telework can be measured using information that reflects local occupational structures.

The findings also have broader policy implications. Although broadband expansion can stimulate economic activity, connectivity alone is unlikely to be sufficient to promote gender equality in the labor market. Policies that expand digital access together with employment in telework-compatible occupations can increase women's access to paid work. Where women's education levels are already high and telecommunications infrastructure is strong, telework provides one channel through which investments in human capital and digital infrastructure can be translated into greater economic participation. The central lesson is that workplace flexibility is produced jointly by local occupational structure and digital infrastructure. Connectivity matters most when it reaches places where existing jobs contain tasks that can be performed remotely or flexibly. In this sense, telework exposure provides a demand-side channel through which digital expansion can make structural transformation more inclusive by expanding access to employment for workers who would otherwise face barriers to conventional workplace participation.

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Appendix

A Derivations for the Theoretical Framework

This appendix provides derivations for the value comparisons discussed in Section 3. To keep the main text focused on intuition and empirical predictions, the algebraic comparisons between telework, office work, and no paid work are collected here.

A.1 Telework versus Office Work

Telework is preferred to office work if

$$V_T > V_O. \tag{37}$$

For expositional simplicity, suppose that both work options require the same hours L. Then the value of telework can be written as

$$V_T = u(y_h + w_T L, \ell_T, f(d_T)) - \tau_T v(L) - \phi z(d_T), \tag{38}$$

where

$$\ell = 1 - L - d_T. \tag{39}$$

The value of office work is

$$V_O = u(y_h + w_O L, \ell_O, f(d_O)) - \tau_O v(L), \tag{40}$$

where

$$\ell = 1 - (1 + t_O)L - d_O. \tag{41}$$

Using a first-order approximation around a common allocation gives

$$V_T - V_O \approx u_c(w_T - w_O)L + u_H\{f(d_T) - f(d_O)\} + (\tau_O - \tau_T)v(L) - \phi z(d_T). \tag{42}$$

If the domestic-time allocation is held fixed for the comparison, then $d_T = d_O$, and the household-production term drops out. Since $\ell_T - \ell_O = t_O L$, telework is preferred to office work if

$$u_c(w_T - w_O)L + u_\ell t_O L + (\tau_O - \tau_T)v(L) - \phi z(d_T) > 0. \tag{43}$$

Rearranging yields

$$w_O - w_T < \frac{u_\ell}{u_c} t_O + \frac{(\tau_O - \tau_T) v(L)}{u_c L} - \frac{\phi z(d_T)}{u_c L}. \tag{44}$$

A.2 Telework versus No Paid Work

Telework is preferred to no paid work if

$$V_T > V_N. \tag{45}$$

The value of no paid work is

$$V_N = u(y_h, \ell, f(d_N)). \tag{46}$$

Using a first-order approximation,

$$V_T - V_N \approx u_c w_T L + u_H \{f(d_T) - f(d_N)\} - \tau_T v(L) - \phi z(d_T). \tag{47}$$

Therefore, telework is preferred to no paid work if

$$u_c w_T L > \tau_T v(L) + \phi z(d_T) + u_H \{f(d_N) - f(d_T)\}. \tag{48}$$

A.3 Office Work versus No Paid Work

Office work is preferred to no paid work if

$$V_O > V_N. \tag{49}$$

Using a first-order approximation,

$$V_O - V_N \approx u_c w_O L + u_H \{f(d_O) - f(d_N)\} - \tau_O v(L). \tag{50}$$

Since office work requires both paid work time and commuting time, the leisure loss relative to no paid work is approximately

$$\ell_N - \ell_O = (1 + t_O) L. \tag{51}$$

Thus, office work is preferred to no paid work if

$$u_c w_O L > \tau_O v(L) + u_\ell (1 + t_O) L + u_H \{f(d_N) - f(d_O)\}. \tag{52}$$

Equivalently,

$$w_O > \frac{\tau_O v(L)}{u_c L} + \frac{u_\ell}{u_c}(1 + t_O) + \frac{u_H\{f(d_N) - f(d_O)\}}{u_c L}. \tag{53}$$

A.4 Comparative Statics

The model implies that an increase in telework exposure raises the relative value of telework by reducing the effective time and mobility cost of paid work. Let F denote telework flexibility. A higher value of F can reduce commuting or mobility costs, so that

$$\frac{\partial t_T}{\partial F} < 0, \qquad \frac{\partial \tau_T}{\partial F} < 0. \tag{54}$$

Since telework has $t_T = 0$ in the baseline setup, the relevant effect of greater telework exposure is to increase the feasibility and attractiveness of the telework option itself. Therefore,

$$\frac{\partial (V_T - V_N)}{\partial F} > 0 \tag{55}$$

whenever flexibility reduces the cost of working more than it increases home-based work frictions. Similarly,

$$\frac{\partial (V_T - V_O)}{\partial F} > 0 \tag{56}$$

when telework reduces commuting, mobility, or workplace-related costs relative to office work.

These comparative statics motivate the empirical analysis: districts with greater telework exposure should experience larger increases in women's paid employment, especially among women for whom office work is more costly because of mobility restrictions, household responsibilities, or commuting constraints.

B Figures

B.1 Comparison between LLM-generated and text classifier approach

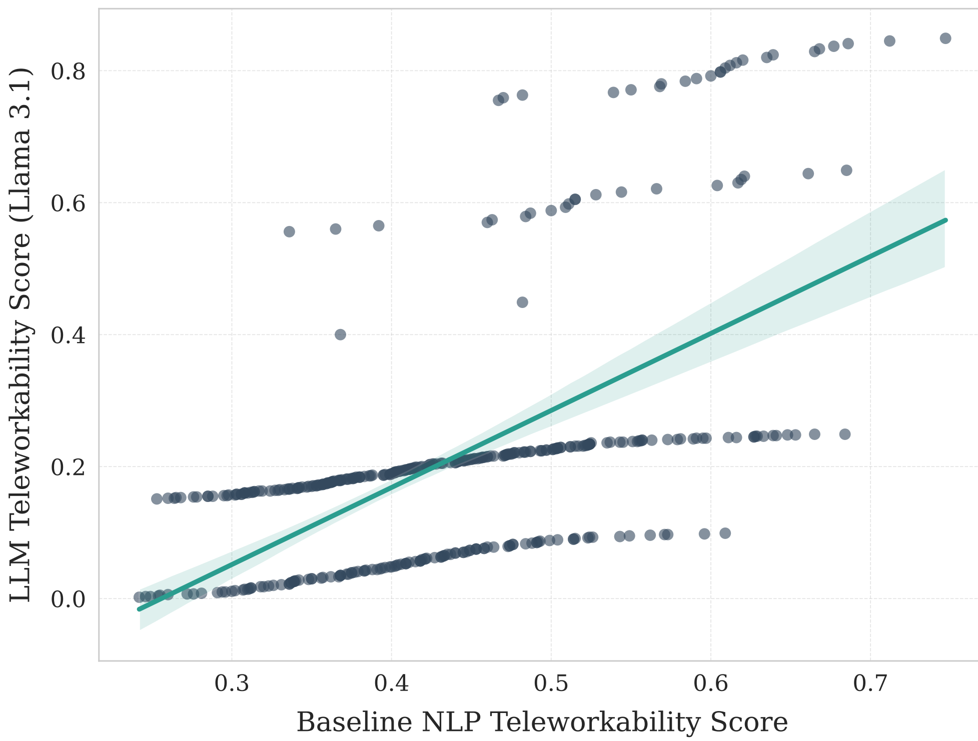
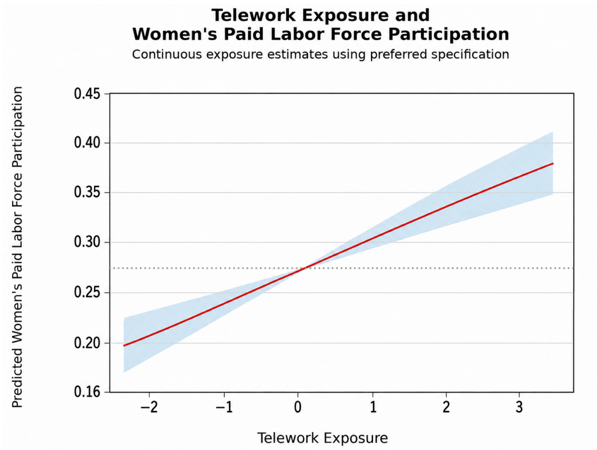
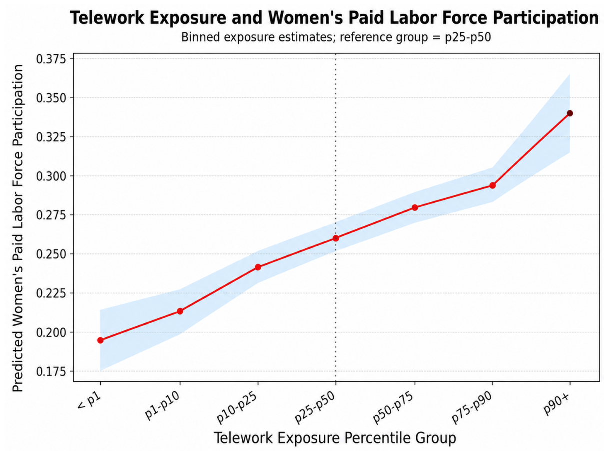


Figure 11. Comparison between NLP and LLM generated telework scores.

B.2 Plots of predicted labor supply by telework exposure



(a) Continuous exposure



(b) Binned exposure

Figure 12. Predicted Effects of Telework Exposure on Female Paid Labor Supply.
Notes: Panel (a) and (b) plots predicted paid labor force participation across the continuous and binned distribution (using p25–p50 as reference bin) of telework exposure. Shaded bands denote 95% confidence intervals. Standard errors are clustered at the district level. Panel 12a confirms a positive, monotonically increasing gradient—the predicted participation rate rises from about 20% at the lowest exposure levels to around 39% at the highest. Panel 12b corroborates this pattern without imposing linearity. It shows that the overall relationship is positive and monotonically increasing. Predicted female labor supply rises linearly when telework exposure rises from 10–25 percentiles to 50–75 percentiles. Thereafter, the predicted female labor force participation steeply beyond 75^{th} percentile of exposure which includes districts such as Northwest Delhi, Chennai, Bangalore, Pune, Thane. Districts in the lowest exposure (≤ 25th percentile) are Ahmedabad, Nadia, Jaipur, Murshidabad, Nagpur, Chittoor. The distribution of districts are depicted in figure 13. Similar patterns can be seen in case of employment participation (Figures **??** and **??**).

B.3 Districts by telework exposure bins

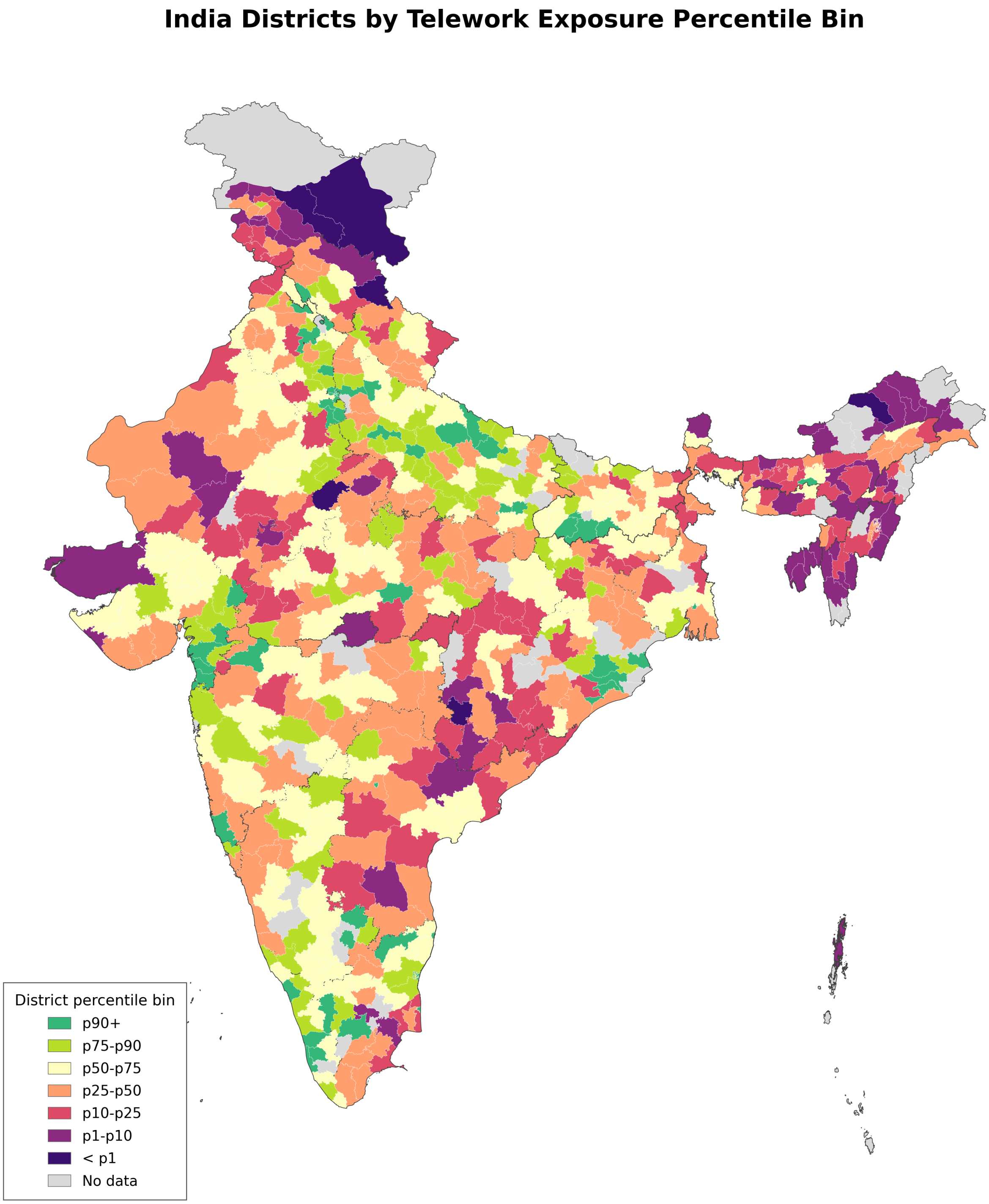


Figure 13. Distribution of Districts by telework exposure bins

B.4 Hypothetical Transmitter Lattice

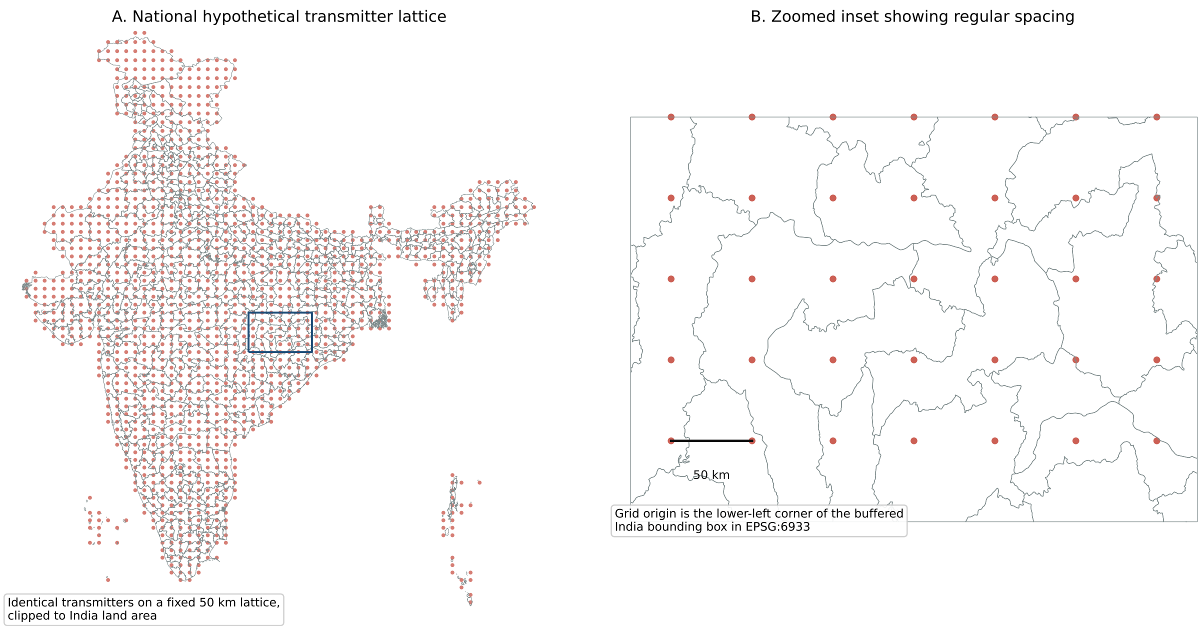


Figure 14. Distribution of hypothetical transmitters across India

C Tables

C.1 Results on the Locked Test Set

Table 9. Locked-Test Performance at Alternative Classification Thresholds

	Threshold	Bal. Acc.	F1	ROC–AUC	PR–AUC
F1-optimal	**0.468**	0.814	0.714	0.902	0.821
Youden-J optimal	**0.468**	0.814	0.714	0.902	0.821

Notes: The F1-optimal and Youden's J-optimal thresholds are selected using out-of-fold predictions from the 250-observation training sample. Both criteria select $\tau = 0.468$. The table reports classification performance on the independent locked test set of 150 occupations. At the training-selected threshold, balanced accuracy is 0.814 and the F1 score for the teleworkable class is 0.714. ROC–AUC and PR–AUC are threshold-independent and therefore remain unchanged across rows. The locked test set is not used for threshold selection.

Table 10. Performance of Text Classifier on the Locked Test Set

	Precision	Recall	F1	N
1 – Teleworkable	0.63636	0.81395	**0.71429**	43
0 – Not teleworkable	0.91579	0.81308	**0.86139**	107
Accuracy			0.81333	150
Macro Average	0.77608	0.81352	**0.78784**	150
Weighted Average	0.83569	0.81333	**0.81922**	150

Notes: This table reports classification performance on the independent locked test set of 150 manually labeled occupations. The classifier is trained on 250 separate manually labeled occupations, and the threshold $\tau = 0.46752$ is selected using out-of-fold predictions from the training sample only. The locked test set is used solely for final validation. See Appendix D.2 for details on the NLP terminology.

C.2 LLM-generated Telework Scores

Table 11. Top 10 and bottom 10 occupations by LLM-generated telework scores

Code	Occupation Title	LLM-generated score	NLP-generated score
Panel A: Top 10 by LLM-generated telework score			
2511.0102	Engineer-Software Transition	1.000	0.695
2412.0200	Financial Analyst	0.988	0.630
2641.0801	Associate-Learning	0.975	0.665
1330.0101	Communication Analyst	0.962	0.615
2519.0501	Quality Engineer	0.950	0.694
3118.0200	Draughtsperson, Civil	0.938	0.417
3521.0511	Sound Editor	0.925	0.597
2512.0205	Junior Software Developer	0.912	0.630
2641.0602	Script Researcher	0.900	0.565
2641.0302	Script Editor	0.888	0.547
Panel B: Bottom 10 by LLM-generated telework score			
8152.0700	Sock Knitter/Knitting Machine	0.002	0.232
7523.1100	Tenoning Machine Operator	0.003	0.226
8131.7000	Tablet Machine Operator	0.005	0.228
8157.0100	Washing Machine Operator	0.006	0.218
8160.8700	Cutting Machine Operator, Tobacco	0.008	0.238
8171.0100	Chipper Man, Paper Pulp	0.010	0.246
8112.0700	Stone Sawyer, Machine	0.011	0.225
8131.4200	Box Making Machine Operator	0.013	0.242
7233.0800	Mechanic, Road Roller	0.015	0.252
8342.0400	Grader Operator	0.016	0.240

Notes: This table reports the top ten and bottom ten occupations ranked by the LLM-generated telework score. The third column gives the LLM-based telework probability, while the fourth column reports the corresponding NLP-generated telework probability for the same occupation. The NLP-generated probabilities are obtained from the latest occupation-level prediction file and are rounded to three decimal places.

C.3 Full regression tables for key results

Table 12. Telework Exposure and Labor Market Participation by Gender: Full Regression Results

	Labor Force Participation		Employment Participation	
	Women	**Men**	**Women**	**Men**
	(1)	**(2)**	**(3)**	**(4)**
Telework exposure	0.0277*** (0.0061)	0.0052 (0.0035)	0.0285*** (0.0057)	0.0060 (0.0037)
Age	−0.0036*** (0.0002)	−0.0112*** (0.0002)	−0.0031*** (0.0002)	−0.0102*** (0.0002)
Education (reference category: Not literate)				
Literate without formal schooling: EGS/NFEC/AEC	−0.0475 (0.0315)	0.0139 (0.0271)	−0.0437 (0.0315)	0.0128 (0.0300)
Literate without formal schooling: TLC	−0.0825** (0.0386)	−0.1227* (0.0726)	−0.0722* (0.0382)	−0.0817 (0.0758)
Literate without formal schooling: Other	−0.0749*** (0.0204)	0.0598*** (0.0204)	−0.0668*** (0.0205)	0.0983*** (0.0203)
Below primary	−0.0078 (0.0058)	0.0384*** (0.0048)	−0.0032 (0.0058)	0.0426*** (0.0054)
Primary	−0.0431*** (0.0052)	0.0465*** (0.0037)	−0.0359*** (0.0052)	0.0524*** (0.0041)
Middle	−0.0970*** (0.0052)	0.0527*** (0.0036)	−0.0861*** (0.0052)	0.0583*** (0.0043)
Secondary	−0.1193*** (0.0058)	0.0204*** (0.0041)	−0.1078*** (0.0059)	0.0289*** (0.0047)
Higher secondary	−0.2016*** (0.0079)	−0.1643*** (0.0053)	−0.1778*** (0.0076)	−0.1329*** (0.0051)
Diploma/certificate course	0.0502*** (0.0121)	0.0289*** (0.0078)	0.0064 (0.0123)	−0.0100 (0.0083)
Graduate	−0.0527*** (0.0077)	0.0015 (0.0041)	−0.0937*** (0.0085)	−0.0461*** (0.0047)
Postgraduate and above	0.0944*** (0.0105)	0.0413*** (0.0054)	0.0276** (0.0113)	0.0072 (0.0062)
Marital status				
Never married	−0.0414 (0.1613)	−0.1179 (0.1855)	−0.1453 (0.1724)	−0.2818 (0.1878)
Currently married	−0.0468 (0.1618)	0.2503 (0.1853)	−0.0831 (0.1723)	0.1875 (0.1877)
Widowed	−0.0658 (0.1618)	0.0124 (0.1853)	−0.1074 (0.1722)	−0.0614 (0.1878)
Divorced/separated	0.1748 (0.1611)	0.1698 (0.1856)	0.1235 (0.1713)	0.0789 (0.1883)

Continued on next page

Table 12. Telework Exposure and Labor Market Participation by Gender: Full Regression Results *(continued)*

	Labor Force Participation		Employment Participation	
	Women	**Men**	**Women**	**Men**
	(1)	**(2)**	**(3)**	**(4)**
Religion (reference category: Hinduism)				
Islam	−0.1012***	−0.0091***	−0.0982***	−0.0165***
	(0.0071)	(0.0030)	(0.0069)	(0.0036)
Christianity	0.0125	−0.0246***	0.0174**	−0.0209***
	(0.0079)	(0.0054)	(0.0070)	(0.0066)
Sikhism	−0.0060	−0.0053	−0.0058	−0.0131
	(0.0070)	(0.0087)	(0.0073)	(0.0090)
Jainism	−0.0535***	0.0435***	−0.0412***	0.0673***
	(0.0151)	(0.0101)	(0.0150)	(0.0113)
Buddhism	−0.0347**	−0.0176	−0.0367**	−0.0244**
	(0.0146)	(0.0111)	(0.0146)	(0.0109)
Zoroastrianism	0.0228	0.0087	0.0431	−0.0353
	(0.0437)	(0.0425)	(0.0464)	(0.0659)
Other religions	0.0262	0.0172	0.0288	−0.0036
	(0.0219)	(0.0124)	(0.0214)	(0.0127)
Social group (reference category: Scheduled Tribe)				
Scheduled Caste	−0.0727***	−0.0047	−0.0726***	−0.0106**
	(0.0093)	(0.0044)	(0.0091)	(0.0053)
Other Backward Class	−0.0612***	0.0077*	−0.0564***	0.0177***
	(0.0091)	(0.0041)	(0.0090)	(0.0048)
Others	−0.0912***	0.0015	−0.0834***	0.0165***
	(0.0095)	(0.0045)	(0.0094)	(0.0053)
Lagged log nightlights	−0.0157	−0.0052	−0.0151	−0.0138
	(0.0266)	(0.0077)	(0.0273)	(0.0104)
Lagged log cell-tower density	−0.0071**	−0.0017	−0.0075**	−0.0024
	(0.0032)	(0.0014)	(0.0030)	(0.0016)
Constant	0.7293**	1.1643***	0.7240**	1.2336***
	(0.3150)	(0.2018)	(0.3281)	(0.2095)
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
State-by-year fixed effects	Yes	Yes	Yes	Yes
Observations	579,340	569,554	579,340	569,554
Clusters	600	600	600	600
R-squared	0.1206	0.2372	0.1118	0.2347
Within R-squared	0.0395	0.2264	0.0310	0.2179

Notes: The table reports the full set of coefficients from the baseline specification reported in Table 4. Columns (1) and (2) use paid labor force participation as the dependent variable, while Columns (3) and (4) use employment participation. Columns (1) and (3) report estimates for women, and Columns (2) and (4) report estimates for men. All specifications include district fixed effects, year fixed effects, and state-by-year fixed effects. Standard errors, clustered at the district level, are reported in parentheses below each coefficient. PLFS sampling weights are used in all regressions. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 13. IV Estimates of Telework Exposure and Women's Paid Labor: Full Regression Results

	(1)	(2)
	First stage	**2SLS**
Dependent variable:	Telework exposure	Paid labor
$TWO_d \times A_d^{ITM} \times 4G_t$	0.7083***	
	(0.0687)	
Telework exposure		0.0846***
		(0.0138)
Age	0.0000	−0.0036***
	(0.0001)	(0.0002)
Education (reference category: Not literate)		
Literate without formal schooling: EGS/NFEC/AEC	0.0462	−0.0504
	(0.0458)	(0.0307)
Literate without formal schooling: TLC	−0.0132	−0.0801**
	(0.0430)	(0.0383)
Literate without formal schooling: Other	0.0330	−0.0770***
	(0.0257)	(0.0204)
Below primary	−0.0014	−0.0079
	(0.0039)	(0.0058)
Primary	−0.0002	−0.0432***
	(0.0030)	(0.0052)
Middle	0.0041	−0.0975***
	(0.0033)	(0.0052)
Secondary	0.0045	−0.1197***
	(0.0036)	(0.0058)
Higher secondary	0.0020	−0.2019***
	(0.0035)	(0.0079)
Diploma/certificate	0.0076	0.0496***
	(0.0088)	(0.0120)
Graduate	0.0019	−0.0527***
	(0.0048)	(0.0077)
Postgraduate and above	0.0055	0.0941***
	(0.0063)	(0.0106)

Notes: Column (1) reports the first-stage regression, with telework exposure as the dependent variable. Column (2) reports the corresponding two-stage least-squares regression for women's paid labor. The free-space signal interacted with 4G growth is included as a control. Both specifications include district fixed effects, year fixed effects, and state-by-year fixed effects and use PLFS sampling weights. Standard errors, shown in parentheses, are clustered by district. The model is exactly identified, with one endogenous regressor and one excluded instrument. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 13. IV Estimates of Telework Exposure and Women's Paid Labor: Full Regression Results (continued)

	(1) First stage	(2) 2SLS
Dependent variable:	Telework exposure	Paid labor
Marital status		
Never married	0.1410	−0.0454
	(0.1503)	(0.1630)
Currently married	0.1461	−0.0512
	(0.1507)	(0.1636)
Widowed	0.1466	−0.0703
	(0.1509)	(0.1635)
Divorced/separated	0.1438	0.1703
	(0.1524)	(0.1628)
Religion (reference category: Hinduism)		
Islam	0.0028	−0.1013***
	(0.0053)	(0.0071)
Christianity	0.0113	0.0115
	(0.0081)	(0.0079)
Sikhism	−0.0109	−0.0045
	(0.0136)	(0.0069)
Jainism	−0.0134	−0.0518***
	(0.0311)	(0.0155)
Buddhism	0.0251	−0.0356**
	(0.0171)	(0.0149)
Zoroastrianism	−0.1077**	0.0280
	(0.0454)	(0.0444)
Other religion	0.0047	0.0259
	(0.0280)	(0.0206)
Social group (reference category: Scheduled Tribe)		
Scheduled Caste	−0.0068	−0.0721***
	(0.0101)	(0.0092)
Other Backward Class	−0.0024	−0.0610***
	(0.0093)	(0.0091)
Other	−0.0066	−0.0905***
	(0.0099)	(0.0096)
Lagged log nighttime lights	0.2629**	−0.0563*
	(0.1030)	(0.0295)
FSS signal × 4G growth	−0.7428	−0.0200
	(0.7130)	(0.0800)
District fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
State × year fixed effects	Yes	Yes
Survey weights	Yes	Yes
Kleibergen–Paap rk Wald F	106.27	
Kleibergen–Paap LM p-value	< 0.001	
Anderson–Rubin p-value		< 0.001
Observations	579,340	579,340

Notes: Column (1) reports the first-stage regression, with telework exposure as the dependent variable. Column (2) reports the corresponding two-stage least-squares regression for women's paid labor. The free-space signal interacted with 4G growth is included as a control. Both specifications include district fixed effects, year fixed effects, and state-by-year fixed effects and use PLFS sampling weights. Standard errors, shown in parentheses, are clustered by district. The model is exactly identified, with one endogenous regressor and one excluded instrument. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 14. IV Estimates of Telework Exposure and Men's Paid Labor: Full Regression Results

	(1) First stage	(2) 2SLS
Dependent variable:	Telework exposure	Paid labor
$TWO_d \times A_d^{ITM} \times 4G_t$	0.6983*** (0.0688)	
Telework exposure		0.0093* (0.0053)
Age	−0.0001 (0.0001)	−0.0112*** (0.0002)
Education (reference category: Not literate)		
Literate without formal schooling: EGS/NFEC/AEC	−0.0526 (0.0374)	0.0143 (0.0271)
Literate without formal schooling: TLC	−0.0060 (0.0400)	−0.1233* (0.0728)
Literate without formal schooling: Other	0.0223 (0.0224)	0.0599*** (0.0204)
Below primary	0.0051 (0.0041)	0.0384*** (0.0048)
Primary	0.0027 (0.0034)	0.0465*** (0.0037)
Middle	0.0011 (0.0035)	0.0527*** (0.0036)
Secondary	−0.0013 (0.0030)	0.0204*** (0.0041)
Higher secondary	0.0046 (0.0038)	−0.1644*** (0.0053)
Diploma/certificate	−0.0022 (0.0068)	0.0289*** (0.0078)
Graduate	0.0010 (0.0045)	0.0015 (0.0041)
Postgraduate and above	0.0075 (0.0070)	0.0412*** (0.0055)

Notes: Column (1) reports the first-stage regression, with telework exposure as the dependent variable. Column (2) reports the corresponding two-stage least-squares regression for men's paid labor. The free-space signal interacted with 4G growth is included as a control. Both specifications include district fixed effects, year fixed effects, and state-by-year fixed effects and use PLFS sampling weights. Standard errors, shown in parentheses, are clustered by district. The model is exactly identified, with one endogenous regressor and one excluded instrument. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 14. IV Estimates of Telework Exposure and Men's Paid Labor: Full Regression Results (continued)

	(1) First stage	(2) 2SLS
Dependent variable:	Telework exposure	Paid labor
Marital status		
Never married	0.2958***	−0.1197
	(0.0947)	(0.1860)
Currently married	0.2963***	0.2485
	(0.0947)	(0.1858)
Widowed	0.2902***	0.0106
	(0.0945)	(0.1858)
Divorced/separated	0.2749***	0.1682
	(0.0956)	(0.1861)
Religion (reference category: Hinduism)		
Islam	−0.0000	−0.0090***
	(0.0054)	(0.0030)
Christianity	0.0131*	−0.0247***
	(0.0078)	(0.0054)
Sikhism	−0.0026	−0.0053
	(0.0134)	(0.0087)
Jainism	−0.0053	0.0436***
	(0.0322)	(0.0100)
Buddhism	0.0304*	−0.0178
	(0.0171)	(0.0111)
Zoroastrianism	−0.0657	0.0091
	(0.0482)	(0.0423)
Other religion	0.0094	0.0172
	(0.0307)	(0.0123)
Social group (reference category: Scheduled Tribe)		
Scheduled Caste	−0.0100	−0.0046
	(0.0105)	(0.0044)
Other Backward Class	−0.0013	0.0077*
	(0.0100)	(0.0041)
Other	−0.0038	0.0015
	(0.0108)	(0.0045)
Lagged log nighttime lights	0.2628**	−0.0097
	(0.1023)	(0.0083)
FSS signal × 4G growth	−0.7096	0.0468
	(0.7141)	(0.0460)
District fixed effects	Yes	Yes
Year fixed effects	Yes	Yes
State × year fixed effects	Yes	Yes
Survey weights	Yes	Yes
Kleibergen–Paap rk Wald F	103.02	
Kleibergen–Paap rk LM statistic	32.96	
Kleibergen–Paap LM p-value	< 0.001	
Anderson–Rubin Wald F		3.01
Anderson–Rubin p-value		0.083
Observations	569,554	569,554

Notes: Column (1) reports the first-stage regression, with telework exposure as the dependent variable. Column (2) reports the corresponding two-stage least-squares regression for men's paid labor. The free-space signal interacted with 4G growth is included as a control. Both specifications include district fixed effects, year fixed effects, and state-by-year fixed effects and use PLFS sampling weights. Standard errors, shown in parentheses, are clustered by district. The model is exactly identified, with one endogenous regressor and one excluded instrument. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

C.4 Robustness Checks

C.4.1 Network Resolutions

Table 15. Sensitivity to Common-Reference Network Resolution

	20% Coarser (1)	**Baseline** (2)	**20% Finer** (3)
Telework exposure	0.0853***	0.0846***	0.0888***
	(0.0144)	(0.0138)	(0.0158)
FSS signal × 4G growth	0.046	−0.002	−0.032
	(0.028)	(0.008)	(0.029)
Individual controls	Yes	Yes	Yes
Lagged nighttime lights	Yes	Yes	Yes
FSS signal × 4G growth	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
State × year fixed effects	Yes	Yes	Yes
Survey weights	Yes	Yes	Yes
First-stage coefficient	0.6934***	0.7083***	0.6474***
Kleibergen–Paap F-statistic	99.71	106.27	81.71
Anderson–Rubin p-value	< 0.001	< 0.001	< 0.001
Observations	579,340	579,340	579,340

Notes: The dependent variable is an indicator equal to one if the surveyed woman engages in paid labor. Each column reports a separate 2SLS specification using the indicated transmitter and receiver grid spacings, measured in kilometers. District-clustered standard errors are reported in parentheses. All specifications use the same estimation sample, controls, fixed effects, probability weights, and clustering level. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.10$.

C.4.2 Alternative Networks

Table 16. Sensitivity to Common-Reference Network Construction

Panel A. Receiver spacing (transmitter spacing fixed at 50 km)	15 km (1)	30 km (2)	40 km (3)
Telework exposure	0.0865***	0.0881***	0.0793***
	(0.0144)	(0.0143)	(0.0134)
FSS signal × 4G growth	−0.0487	−0.0210	0.0407*
	(0.0503)	(0.0195)	(0.0240)

Panel B. Transmitter spacing (receiver spacing fixed at 20 km)	30 km (1)	40 km (2)	60 km (3)	70 km (4)
Telework exposure	0.0841***	0.0793***	0.0875***	0.0883***
	(0.0147)	(0.0151)	(0.0149)	(0.0147)
FSS signal × 4G growth	0.0175	−0.0039	0.0137	0.0305
	(0.0225)	(0.0142)	(0.0224)	(0.0381)

Panel C. Grid origin (spacings fixed at 50 km and 20 km)	TX shifted (25, 25) (1)	RX shifted (10, 10) (2)	Both shifted (25, 25); (10, 10) (3)
Telework exposure	0.0885***	0.0872***	0.0881***
	(0.0149)	(0.0144)	(0.0151)
FSS signal × 4G growth	−0.0322	−0.0315	−0.0660
	(0.1135)	(0.0294)	(0.1048)
Individual controls	Yes	Yes	Yes
Lagged nighttime lights	Yes	Yes	Yes
District, year, and state × year FE	Yes	Yes	Yes
Survey weights	Yes	Yes	Yes
Observations	579,340	579,340	579,340

Notes: Each column reports a separate 2SLS specification that differs only in how the hypothetical common-reference transmitter and receiver network is constructed. Panel A varies receiver spacing holding transmitter spacing at 50 km; Panel B varies transmitter spacing holding receiver spacing at 20 km; Panel C holds both spacings at their baseline values (50 km and 20 km) and shifts the origin of the transmitter lattice, the receiver lattice, or both, with shifts in kilometers reported in the column headers. Every column uses the same estimation sample (579,340 observations and includes individual controls, lagged nighttime lights, district, year, and state-by-year fixed effects, PLFS survey weights, and the free-space signal measure interacted with national 4G growth. The baseline construction—50 km transmitter spacing, 20 km receiver spacing, and no origin shift—is the specification reported in Table **??** and is not repeated here; it yields a coefficient of 0.0846 (0.0138). Standard errors, clustered at the district level, are reported in parentheses. $^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.10$.

C.4.3 Excluding COVID-19 years

Table 17. IV Estimates by Excluding COVID-19 Pandemic years (2020-21)

	(1)	(2)
	First stage	2SLS
Dependent variable:	Telework exposure	Paid labor
$TWO_d \times A_d^{ITM} \times 4G_t$	0.6986***	
	(0.0673)	
Exposure$_{dt}$		0.0838***
		(0.0150)
FSS signal × 4G growth	−0.0539	−0.1013
	(0.8139)	(0.0826)
Individual controls	Yes	Yes
Lagged nighttime lights	Yes	Yes
FSS signal × 4G growth	Yes	Yes
District fixed effects	Yes	Yes
State × year fixed effects	Yes	Yes
Survey weights	Yes	Yes
Kleibergen–Paap rk Wald F	107.69	
Kleibergen–Paap rk LM p-value	< 0.001	
Anderson–Rubin Wald F		29.46
Anderson–Rubin p-value		< 0.001
Observations	443,002	443,002

Notes: Column (1) reports the first-stage estimate. Column (2) reports the corresponding two-stage least-squares estimate for women's paid labor. All specifications control for the corresponding interaction constructed using free-space signal strength, lagged nighttime lights, and individual characteristics including age, education, marital status, religion, and social group. District and state-by-year fixed effects are included. PLFS sampling weights are used in all specifications, and standard errors, reported in parentheses, are clustered at the district level. The model is exactly identified. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

C.4.4 Additional Robustness Checks

Table 18. Additional Robustness Checks

	Lagged Female Labor Supply	District Representativeness	Sub-samples	
			Ages 18–44	Ages 19–59
	(1)	(2)	(3a)	(3b)
Telework exposure	0.0396***	0.0864***	0.0760***	0.0919***
	(0.0095)	(0.0143)	(0.0137)	(0.0148)
Lagged district female labor participation	1.0428***	—	—	—
	(0.0375)			
FSS signal × 4G growth	−0.0087	−0.0302	−0.0576	−0.0231
	(0.0521)	(0.0861)	(0.0776)	(0.0834)
District-year observations > 50	No	Yes	No	No
Individual controls	Yes	Yes	Yes	Yes
Lagged nighttime lights	Yes	Yes	Yes	Yes
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
State × year fixed effects	Yes	Yes	Yes	Yes
Survey weights	Yes	Yes	Yes	Yes
KP rk Wald F	109.85	98.60	106.69	104.00
Anderson–Rubin Wald F	13.31	31.43	30.97	34.71
Anderson–Rubin p-value	< 0.001	< 0.001	< 0.001	< 0.001
Observations	579,340	570,746	368,299	485,821

Notes: The table reports 2SLS estimates of the effect of telework exposure on women's paid labor. Column (1) controls for lagged district-level female labor-force participation. Column (2) restricts the sample to district-year cells with more than 50 observations. Columns (3a) and (3b) restrict the sample to women ages 18–44 and 19–59, respectively. Telework exposure is instrumented by the interaction of predetermined district teleworkability, terrain-adjusted predicted signal strength, and 4G growth. All specifications control for the corresponding free-space signal interaction, lagged nighttime lights, and individual characteristics, and include district, year, and state-by-year fixed effects. PLFS sampling weights are used. Standard errors in parentheses are clustered by district. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

D Construction of Telework Scores using Supervised Text Classifier

D.1 Evidence-tag dictionary of phrases

Table 19. Evidence tags used to flag tasks typically requiring digital cues and physical presence

Tag	Type	Phrase family (keywords/phrases)
digital_cues	remote_compatible_cues	email / e-mail; computer; software; data; database; Excel; spreadsheet; report; documentation; typing; correspondence; office; online; internet
wc_violent_weekly	physical_presence_flag	police; security guard; guard; prison; patrol; riot; violent; bouncer; law enforcement
wc_outdoors_daily	physical_presence_flag	outdoor; field work / fieldwork; on-site; construction site; farm; harvest; cultivation; mine / mining; forest; road; irrigation
wc_disease_weekly	physical_presence_flag	hospital; clinic; nurse; patient; ward; laboratory / lab; infection; disease; specimen; pathology
wc_minor_injuries_weekly	physical_presence_flag	weld / welding; cutting; grind / grinding; saw; chisel; drill; hammer; nail; sander; burns; chemicals; machine tool; foundry
wc_walkrun_majority	physical_presence_flag	patrol; beat duty; walking; running; foot patrol
wc_ppe_majority	physical_presence_flag	protective; PPE; safety equipment; helmet; gloves; goggles; mask; respirator; harness
gwa_general_physical_important	physical_presence_flag	manual work / manual labor; physically demanding; lifting; carrying; digging; pulling; pushing; carpenter / carpentry; mason / masonry; brick / bricklaying; stone; timber; joiner / joinery; plaster; roofer / roofing

Table 19. Evidence tags used to flag tasks typically requiring digital cues and physical presence (continued)

Tag	Type	Phrase family (keywords/phrases)
gwa_move_objects_important	physical_presence_flag	load / loading; unload / unloading; lift / lifting; carry / carrying; stack / stacking; pack / packing; shipment; warehouse; cargo; materials handling; forklift
gwa_control_machines_important	physical_presence_flag	machine / machinery; plant; boiler; CNC; lathe; press; mill; operate equipment; process control
gwa_operate_vehicles_important	physical_presence_flag	driver / driving; vehicle; truck; bus; forklift; crane; tractor; excavator; delivery van
gwa_public_direct_important	physical_presence_flag	counter; front desk; reception; cashier; waiter; server; retail; shop; hotel; restaurant; attending customers; public dealing
gwa_repair_mech_important	physical_presence_flag	repair; maintain; maintenance; service / servicing; fitter; mechanic; overhaul
gwa_repair_elec_important	physical_presence_flag	repair / maintain / service with: electric / electrical; electronics; wiring; circuit; appliance; PLC
gwa_inspect_important	physical_presence_flag	inspect / inspection; quality control; QC; testing; test; checking; calibration

Notes: Phrase families are shown in readable form. In the implementation, each family is encoded as a regular-expression (regex) pattern to capture common variants (e.g., plurals, hyphenation, spacing). These evidence tags are used for interpretability and error audits; they do not mechanically determine the final teleworkability label.

D.2 NLP Terminology

Precision tells us how many results were actually positive out of those classified as positive by the model. The corresponding equation is:

$$\text{precision} = \frac{\text{True Positives}}{\text{True Positives+False Positives}} \tag{57}$$

Recall tells us how many of the positive cases the trained classifier accurately predicted in the data. The corresponding equation is:

$$\text{Recall} = \frac{\text{True Positives}}{\text{True Positives+False Negatives}} \tag{58}$$

Specificity tells us how well the model avoids false alarms. It is measured as:

$$\text{Specificity} = \frac{\text{True Negatives}}{\text{True Negatives+False Negatives}} \tag{59}$$

Sensitivity tells us how well the model correctly identifies truly positive cases. It is measured as:

$$\text{Sensitivity} = \frac{\text{True Positives}}{\text{True Positives+False Negatives}} \tag{60}$$

F1 Score is the harmonic mean of Precision and Recall. It is calculated as:

$$\text{F1} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision+Recall}} \tag{61}$$

F1 $\in$ [0,1]. If F1=1, it is the ideal case of no false positives and no false negatives. In practice, F1 above 0.9 is considered efficient.

Youden's J statistic selects the cutoff that maximizes the joint classification accuracy of true positives and true negatives.It is calculated as:

$$\mathbf{J} = \text{Sensitivity+Specificity-1} \tag{62}$$

Any value τ that maximizes eq. (62) is the optimal threshold choice.

D.2.1 Robustness Check: LLM-Based Teleworkability Scores

This appendix describes the procedure used to generate an alternative teleworkability measure using a large language model (LLM). The objective is to assess whether the occupation-level teleworkability patterns identified using the baseline NLP classifier are robust to an independently generated scoring approach.

Sampling of Occupations I randomly draw a sample of 400 occupations from the full NCO–2015 occupation set used in the baseline analysis. For each occupation, I use the occupation title and detailed description from the NCO manual as input text. These occupations are the same textual inputs used by the baseline NLP pipeline described in Section **??**. The sampling procedure ensures that the robustness exercise covers a diverse set of occupations across sectors and skill levels while keeping the computational cost of LLM evaluation manageable.

LLM Scoring Procedure Teleworkability probabilities are generated using a locally hosted `llama3.1:8b` model accessed through the Ollama inference framework. For each occupation, the model is prompted with the occupation title and description and instructed to return a single teleworkability probability between zero and one.

The prompt explicitly requires the model to return a strict JSON object with a single key `telework_prob`. The model is instructed to interpret the probability as follows:

- 0: the occupation cannot realistically be performed remotely,
- 1: the occupation can be fully performed remotely.

To ensure consistency across responses, several constraints are imposed in the prompting procedure:

1. The model is instructed to output probabilities with three decimal places.
2. The sampling temperature is set to 0.15 to reduce response variability.
3. The output format is restricted to JSON to facilitate automated parsing.

Each occupation is queried sequentially through the Ollama API. The returned responses are parsed using a custom extraction function that retrieves the teleworkability probability from the JSON output and constrains the value to the interval $[0, 1]$.

Handling of LLM Outputs The raw LLM responses occasionally contain formatting variations or coarse probability values. To address this, I implement a parsing procedure that extracts the probability value from the returned JSON string and rounds it to three decimal places. If the response contains a probability rounded to a single decimal (e.g., 0.8), the query is automatically repeated with a stricter formatting instruction.

All extracted probabilities are stored together with the occupation identifier and raw LLM response to allow verification and reproducibility.

Comparison with the Baseline NLP Measure The LLM-generated teleworkability scores are compared with the baseline NLP-based probabilities estimated in the main analysis. Two types of comparisons are performed.

First, I compute Pearson and Spearman correlations between the LLM-based and NLP-based teleworkability probabilities across the sampled occupations. These statistics measure the degree to which the two scoring methods rank occupations similarly.

Second, I evaluate both measures on the subset of occupations that overlap with the manually labeled gold-standard dataset used to train the baseline classifier. On this overlap sample, I compute the area under the receiver operating characteristic curve (ROC–AUC) and the area under the precision–recall curve (PR–AUC) for each scoring method.

These metrics provide a common benchmark for assessing how well each scoring procedure recovers the manually labeled teleworkability classification.

Implementation Details All LLM queries are executed locally using the Ollama inference server (`http://localhost:11434`). The robustness script is implemented in Python and performs the following steps:

1. Randomly sample occupations from the prediction dataset.
2. Query the LLM with the occupation title and description.
3. Parse the returned probability from the JSON response.
4. Store both the extracted probability and raw model output.
5. Compute correlation and classification metrics relative to the baseline NLP score and the gold-standard labels.

The complete code used to generate the LLM scores and evaluation metrics is provided in the replication package.