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

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Abstract

In many emerging economies, social norms encourage women to stay at home and existing jobs often involve long hours and on-site work arrangements. *Can rise of telework pull women into labor market in such countries?* I explore this research question in India where traditional norms are predominant and female labor force participation is low. Telework requires two ingredients: jobs that can be done remotely and the digital infrastructure to do them. Since India lacks task surveys like O*NET in United States, I first classify Indian occupations as teleworkable or not using supervised text methods on detailed descriptions from the national occupation manual. Then, I combine each district's share of teleworkable occupations with lagged cell tower density to measure local exposure to telework. Using nationally representative PLFS data from 2017–2024, I find that a one-standard-deviation increase in telework exposure raises women's paid labor force participation by 1.7 percentage points. Falsification tests and a shift-share instrumental design based on cheap 4G internet expansion further strengthen causal interpretation. The effects are larger among woman who are married, have young children, whose husband are in "greedy jobs" and live in districts with high gender-based violence. I also find that the effects are concentrated among women with technical college degrees and those coming from households with higher economic status. Welfare analysis shows that the public investment in digital connectivity can further unlock women's gains from telework. The benefit-cost ratio exceeds 6-to-1, and net annual earning gains of women being $1.94 billion.

Keywords: Female labor force participation; telework; workplace flexibility; digital infrastructure; gender; India.

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1 Introduction

In many emerging economies, several women remain out of the labor market even when they are able to work. Despite rapid economic growth, female labor force participation (FLFP) remains consistently below the global average in South Asian and Middle East countries (ILO, 2025; World Bank, 2025), as shown in figure 1. Such latent female workforce has precarious consequences not only for socioeconomic well-being of women and young girls but also for total factor productivity of an economy. Even though higher female labor supply is associated with poverty reduction, and improving intergenerational social indicators such as health and education (Amoah et al., 2023; Amolegbe et al., 2025; Galassi et al., 2024; Lopez-Acevedo et al., 2021), women are often confined to unpaid household chores in developing countries. India provides a salient puzzle: despite rise in women's educational attainment, decline in fertility and rise in digital connectivity, gender gap in paid work remains staggering at 45.2 percentage points (ILO, 2025). This is captured in figure 2.

According to Goldin (1995), FLFP has a U-shaped relationship with economic development. At low levels of development, women often work as agricultural laborers or unpaid workers in family-owned farms. As economies expand and per capita income grows, women's employment decline because new mechanization and structural transformation reduce labor demand in agriculture, generate jobs which are incompatible with domestic responsibilities and FLFP declines (Goldin, 1995; Mehrotra and Parida, 2017). As women become more educated and the value of their time increase in labor markets at later stages, they enter in white-collar jobs against which no social stigma holds (Goldin, 2014). In India, however, the sectors that expanded during periods of economic growth did not necessarily generate enough jobs that women could access or that were viewed as socially acceptable (Deshpande & Kabeer, 2024; Klasen & Pieters, 2015). This demand-side interpretation is central to this paper: women's labor supply may depend not only on their education or household characteristics, but also on whether the local economy offers work that can be done under lower mobility, commuting, and time costs.

This paper examines whether exposure to telework increases women's paid labor supply in India. I define telework exposure as the interaction between a district's pre-existing share of teleworkable occupations and local digital infrastructure. The central idea is that neither component is sufficient on its own. Digital connectivity may not increase women's work if the local occupational structure consists mainly of tasks that require physical presence. Similarly, teleworkable occupations may not generate flexible work opportunities if internet access is too limited. Telework exposure should therefore matter most in places where digital infrastructure and occupational compatibility coincide. Using nationally representative data from the Periodic Labor Force Survey (PLFS) durign 2017-2024, I examine effect of telework exposure on female labor supply. To identify causal effects, I matched individual's district of dwelling with the corresponding nighttime lights data to control for local development trends. I exploit time-varying districtwise variation in telework exposure to identify causal effects, accounting for location and time fixed effects. Furthermore, I also include state-year fixed effects to control for state-level policies, such as cash transfer programs targeted towards women's well-being that may influence a woman's participation in labor market.

The baseline two-way fixed effects (TWFE) model shows that a one-standard-deviation increase in telework exposure raises female paid labor force participation by 2.0 percentage points. The estimate remains consistent (1.6–1.7 percentage points) after controlling for lagged nightlights, state-by-year fixed effects, demographic characteristics, alternative definitions of teleworkability, 4G-specific tower exposure, and restrictions to better-sampled district-year cells. The effect is economically meaningful, given that less than one-third of the adult female population are engaged in paid labor. One caveat of this analysis is that the PLFS data is not district-representative. So far in my knowledge, however, there exists no other publicly available district-representative data sources which give information about individual-level occupation description. I address this limitation by testing the sensitivity of baseline analysis using (a) various minimum shares of surveyed administrative units (1%–25%); (b) only those districts with more than 50 observations per district in each year (Peters et al., 2025). In both cases, the results remain consistently similar with the baseline estimates. Heterogeneous effects show that the effects are concentrated among groups for whom household and mobility constraints are likely to be more binding. More specifically, I find larger effects among women with young children but no significant effects among unmarried women, and stronger effects among women who reside in districts with high incidence of reported gender-based violence. Moreover, husband's nature of occupations matter. If a husband is engaged in "greedy jobs", women are more positively responsive to telework exposure. Instead of overall college education alone, I find that the effects are stronger for women with technical degrees and insignificant for those with college degrees in non-technical areas. Furthermore, I find that telework exposure reduces women's unpaid household labor as primary activity and improves their monthly earnings.

One potential threat to validity is omitted variable bias since digital connectivity is likely to be correlated with other district characteristics, which is otherwise difficult to control for. I address this concern in two ways: first, I conduct falsification tests using placebo outcomes, namely, men's paid labor, underage labor force participation and time-varying economic expansion indicators, specifically, bank branch density and economic growth. The effects are negligible and statistically insignificant. To strengthen the causal interpretation, I also exploit rapid nationwide expansion of cheap 4G internet following the Reliance Jio's entry in Indian telecommunications market. I construct a shift-share instrument for my baseline telework exposure that combines predetermined district-level teleworkability with national growth in 4G internet. Both reduced form and IV estimates show that women's paid labor rises in districts with higher baseline teleworkability when 4G connectivity expands. I find three mechanisms that can explain this relationship, namely, computer ownership, internet access and freedom of movement.

The welfare implications are significant. Expanding 4G internet infrastructure costs each district \$362 million per year while yielding aggregate benefits of \$2.31 billion in terms of women's average annual earnings. This generates net benefits of \$1.94 billion and a benefit-cost ratio of 6.37. These estimates justify public investment in digital infrastructure for women's economic well-being. However, these calculations exclude backhaul costs and do not capture non-pecuniary characteristics of each district such as social norms.

This study is one of the first papers to provide nationally representative evidence in an emerging economy. Existing studies have largely focused on the relationship between remote work and women's paid labor in advanced economies (e.g., Arntz et al., 2022; Dettling, 2016a; Harrington and Kahn, 2025). Two recent randomized controlled trials in two Indian cities show that women prefer remote working arrangements (Ho et al., 2024; Jalota & Ho, 2024). This paper asks whether the same mechanism operates at scale: do women enter paid work when their local labor market becomes more exposed to telework? By combining nationally representative data with district-level variation in teleworkable occupations and digital infrastructure, I provide evidence on the broader labor-market effects of telework exposure rather than short-run take-up of experimentally offered jobs. One central feature of such emerging economies is uneven internet penetration. Low internet access limits job information, matching and participation. I account for this in my telework exposure measure by combining occupation-based telework scores with internet penetration in each service area during a given year.

A central contribution of this paper is construction of a novel measure of telework exposure for India. Because India does not have nationally representative task surveys like O*NET in United States and applying U.S.-based telework classifications to developing countries can introduce measurement error through crosswalks and context-specific differences in job tasks (Blázquez et al., 2023; Dingel & Neiman, 2020), I utilize a supervised text classification approach to identify telework potential of each occupation from 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.

This paper contributes to three strands of literature on the role of *flexibility* on women's labor supply. A growing literature shows that workplace flexibility can relax constraints on women's paid work, but the source of flexibility differs. One source is the structure of the job itself. Goldin and Katz (2011) show that high-powered occupations impose pecuniary penalties for family-related amenities such as part-time work, career interruptions, and flexibility during the workday. Goldin (2014) further argues that the remaining gender gap in labor-market outcomes is closely tied to the way jobs reward long, continuous, and particular hours of work. Temporal inflexibility creates a cost of combining career with family. A second source of flexibility comes from alternative work arrangements offered by firms. Mas and Pallais (2017) show that workers value some forms of flexibility, especially work-from-home and protection from unpredictable employer-controlled scheduling, although the average willingness to pay for schedule flexibility alone is more limited. In a randomized experiment, Bloom et al. (2024) find that hybrid work arrangements reduced women's quit rates by one-third and increased job satisfaction in China. A third source of flexibility is infrastructure. Dettling (2016a) shows that high-speed home internet increases labor force participation among married women in the United States, with the largest effects among college-educated married women with children. The proposed mechanisms are job search, telework and time saved in home production.

2 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 et al., 2021; Trougakos et al., 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.

2.1 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:

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

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 $r \in (O, T)$,

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

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.

2.2 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.

2.2.1 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.

2.2.2 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.

2.2.3 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 (e.g., due to safety, geography).

3 Data

I mainly use two data sources for socioeconomic and labor market variables: Periodic Labor Force Survey (PLFS) and the National Family Health Survey (NFHS), both conducted by the Ministry of Statistics and Program Implementation (MoSPI). Figure 3 illustrates geographical coverage of datasets. Panel (a) shows districts which are consistently covered by PLFS during 2017-2024 while Panel (b) depicts districts which are surveyed by both rounds of NFHS during 2015-16 and 2019-21. While some new districts were created during the long span of seven years (2017-2024), I use district classifications from 2011 Census to maintain consistency across PLFS and NFHS survey rounds. In the following subsections, we provide a description of each data sources.

3.1 Periodic Labor Force Survey.

This is a nationally representative survey that covers information on employment, income, socioeconomic and demographic characteristics for over 100,000 urban and rural households. In total, these data include nearly 400,000 individuals. The survey covers whole India except for the villages in Andaman and Nicobar Islands, mainly due to communication constraints. PLFS is conducted annually and is organized in 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. It divides the Indian population into two types of regions, rural and urban. PLFS is representative of rural and urban areas within each National Sample Survey (NSS) Region (a subdivision of state). New urban and rural panels are added each quarter. However, rural households are only visited once, while urban households are revisited quarterly for a total of four quarters. After this, they drop out of the sample. In our analysis, we utilize all rural data and the first visit of each urban household, converting the data into a representative repeated cross-section.

PLFS defines employment 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. An individual is considered to be employed as a principal activity (UPAS), if they report being employed for 365 days before the survey. An individual is said to be employed as weekly activity status (CWS) if they report being employed for 7 day reference period prior the survey. I use this measure of labor force participation to capture corresponding year estimates.
In PLFS, income is reported conditional on employment status. Income is reported from three sources of employment: (i) regular wage or salary, (ii) casual/daily wage, and (iii) self-employment. Income from regular wage employment is asked for the last month; income from self-employment is asked for the last 30 days; and income from casual wage employment is asked for the past week. In order to make all the three sources of income comparable, we construct a monthly measure of income from regular wage or salary, and for income from self-employment by combining the three measures of income for each individual.

Note that PLFS data utilizes sampling weights (known as multipliers) to 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 $\neq$ NSC), the final weight is calculated as (MLTS/200).

Table 1 presents summary statistics for PLFS datasets, focusing on women aged above 18 years old using the PLFS sample from 2017 to 2024. The average female paid labor force participation rate is 28.7 percent which implies that fewer than one-third of adult women in the sample report being engaged in paid work under the current weekly status definition. The average age of women in the sample is approximately 41 years, with a standard deviation of 15.6 years. Average monthly per capita consumption expenditure is Rs. 2,679.6 (27.98 USD), with a standard deviation of Rs. 2,721 (28.42 USD). The latter suggests considerable heterogeneity in household economic status. On an average, women report 10.0 hours of paid labor per week. Earnings also differ by type of employment. Average regular wage earnings are Rs. 1,150.2 (12.01 USD), while average self-employment earnings are Rs. 740.9 (7.74

USD). Weekly casual wage earnings are much lower on average, at Rs. 36.3 (0.38 USD). Both working hours and earnings depict substantial standard deviations which reflect that several women are out of the labor force.

3.2 National Family Health Survey.

National Family Health Survey (NFHS) is a nationally representative, cross-sectional demographic health survey which was part of the global Demographic and Health Survey (DHS) program. The survey is implemented by the International Institute for Population Sciences (IIPS), Mumbai, under the supervision of the Ministry of Health and Family Welfare (MoHFW), Government of India. The sample is drawn using stratified random sampling[1]. In this paper, I utilize the latest two rounds of NFHS data. A women's questionnaire was administered to all eligible women aged 15–49 residing in 601,509 and 636,669 sampled households during the 4th round (NFHS-4) and 5th round (NFHS-5). About 699,686 eligible women were covered in the 4th round (NFHS-4) and 724,115 eligible women in the 5th round (NFHS-5). It collected detailed information on various aspects of gender and household dynamics, including demographic characteristics, fertility and contraception, nutrition, marriage, sexual behaviour, employment, experiences of domestic violence, mobility, and autonomy. However, certain topics, such as sexual behaviour, attitudes and experiences of domestic violence, were included only in a randomly selected subsample of about 15 percent of households through a state-specific module. Following the World Health Organization's ethical guidelines for collecting data on domestic violence, only one eligible woman per household was randomly selected to participate in the domestic violence module. The module was administered to 72,320 women, with strict procedures to ensure respondents' privacy during the interview process. In this paper, the outcome variables are derived from type of occupation, current work status, access to internet, access to computer and freedom to move outside home by oneself.

Table 1 reports summary statistics of continuous and dummy variables in case of women aged above 18 years using both rounds of NFHS datasets. On an average, women's participation in non-agricultural labor is 17.7% which suggests that less than one-fifth of reported adult women are in paid labor other than in agricultural sector. Average age of women in the sample is 30 years which is much lesser than in PLFS because the age group of surveyed women is 15-49 years. Average shares of households with access to internet and at least one computer are 34.1% and 9.0% respectively but both of them has relatively high standard deviation. This implies that there exists substantial variation in terms of digital connectivity across households. Nearly 50% of surveyed women, on an average, have completed middle school or secondary education but mean shares of women with higher secondary and above education levels is merely 12.2%. Typically, 42.3% of women are allowed to go by themselves to market, health facility and outside their locality but the standard deviation is quite high (0.494).

[1] See International Institute for Population Sciences (IIPS) for more details on the survey methodology.

3.3 Construction of Telework Exposure

I examine teleworkability of each occupation described in the National Classification of Occupations of India (NCO, 2015). This manual classifies and codes occupations to align with the International Standard Classification of Occupations (ISCO-08). It uses an 8-digit coding structure in which the first four digits are mapped with the ISCO-08 structure: first digit denotes the major group; the first two digits the sub-major group; the first three digits the minor group and the first four digits the unit group. A decimal thereafter gives detailed job roles within each unit and link to competency framework under the national occupational standards. This occupation manual covers 3,448 8-digit specific occupations.

A widely used benchmark measure was proposed by Dingel and Neiman (2020), who use 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 Dingel and Neiman (2020)'s telework scores to other economies using occupational crosswalks (e.g., Anghel et al., 2020; Palomino et al., 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 et al., 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 et al., 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 countries (e.g., India, China) lack task-based surveys. This is shown in Figure 4.

These concerns are particularly relevant for emerging economies, where occupational structures and work practices differ substantially from those in the United States and covered by OECD PIAAC and STEP surveys. Moreover, telework may have untapped potential in emerging economies where social norms limit women's from working outside. Recent experimental evidence suggests that workers, especially women place high value on remote and hybrid work arrangements in India and China (Bloom et al., 2024; Ho et al., 2024; Jalota & Ho, 2024). In the absence of a credible occupation-level telework measures, it is difficult to study how exposure to telework affects labor market outcomes such as employment resilience, welfare, and gender inequality in emerging economies.

3.3.1 Manual Labeling and Text Classification

Due to lack of task-based survey in India, I rely on text-based information in the occupation manual (NCO, 2015b) using natural language processing model (NLP). I first manually label 249 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. Note that I create a locked test set of 49 manually labeled occupations which is held out entirely from training model. The objective is to see how well the classifier performs on occupations it has never seen before. I then apply the fitted classifier to predict telework scores p_o for all remaining unlabeled 8-digit occupations in the NCO 2015. 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 et al., 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 0.475 (Appendix 33) with an accuracy of 0.97 (Table 34). See Appendix B.3 for details about NLP terms. Using the training set ($N = 49$), I also construct the confusion matrix to compare the manually assigned values with the model generated values. The objective is to see how correctly the model predicted teleworkability of occupations. As shown in Table 35, the model makes 96.9% accurate predictions (i.e., true negatives and true positives) and nearly 3% false cases.

Figure 5 shows the distribution of telework scores. I classify each 8-digit occupation as teleworkable if it exceeds the threshold of optimal F-1 value (i.e., 0.475) that best balances false positives and negatives. Based on this classification, 36.6% of Indian occupations (8-digit NCOs) have high telework potential. 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 ($Pr(TW) > 0.7$). These include software engineer, product designer, technical writers, management and market researchers. On the contrary, least teleworkable jobs ($0.2 < Pr(TW) < 0.25$) 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.

External Validation. To validate my ML-based binary telework indicator, I compare these with the benchmark Dingel & Neiman (DN) (2020) which is based on U.S. ONET job tasks. I construct a crosswalk between Indian NCO(2015a) occupations and U.S. SOC/O*NET occupations by comparing the standardized texts. Titles are lowercased, stripped of stop-words and punctuation, and matched using a similarity score (70% token-set ratio, 30% partial ratio). For each Indian occupation, I retain the single best-scoring U.S. occupation. Matches with similarity scores above 80 are treated as reliable matches. Details of the matching algorithm are provided in Appendix B.4. Using this procedure, 773 out of 3,448 Indian occupations (22.4%) are matched to a U.S. O*NET occupation with sufficiently high title similarity. Within the matched subsample, 358 occupations (46.3%) are classified as teleworkable by ML, compared to 194 occupations (25.1%) classified as teleworkable under Dingel & Neiman (DN) (2020). The confusion matrix is shown in Table 12.

In cases where the ML model predicts teleworkable but DN does not ($ML = 1$, $DN = 0$), the disagreement can reflect genuine task-content differences across contexts: the Indian NCO text may frame a role as largely planning, coordination and documentation-heavy, while the closest U.S. ONET counterpart is coded as requiring on-site presence under the DN task-based criterion. For instance, *Manager, Traffic* (NCO 1324.06) is teleworkable under ML ($Pr(TW) = 0.622$; $ML = 1$) but its best-matched ONET occupation is *Shipping, Receiving, and Traffic Clerks*, which is DN non-teleworkable ($DN = 0$) at this match. Similarly, *Energy Auditor* (NCO 3119.06) is ML teleworkable ($Pr(TW) = 0.631$; $ML = 1$) but the best-matched O*NET title is *Energy Auditors*, which DN codes as non-teleworkable ($DN = 0$), consistent with DN treating auditing as involving physical site inspection even when reporting components exist. These examples are plausible cases where the same occupational label can embed different mixes of fieldwork vs. office-based analysis across countries, creating structural disagreement rather than pure classification noise.

Conversely, when DN predicts teleworkable but ML does not ($DN = 1$, $ML = 0$), disagreement often reflects limitations of title-based crosswalks. Some Indian occupations match most closely to broad U.S. managerial or professional titles that DN classifies as teleworkable, even though the Indian occupation description contains explicit public-facing, enforcement, or physical components. For instance, Shop Attendant/Sales Assistant (NCO 5211.02) is classified as non-teleworkable by ML ($Pr(TW) = 0.444$) but is matched to Sales Managers (DN = 1). Likewise, Supervisor, Customs (NCO 3351.02) is ML non-teleworkable ($Pr(TW) = 0.447$) but matches to Customs Brokers (DN = 1). In both cases, the Indian occupation appears operational or field-based, whereas the matched U.S. occupation is more desk-oriented.

Robustness Check. Using a large language model (LLM), I construct an alternative set of telework scores at occupation level. Specifically, I provide the open-source `Llama 3.1 (8b)` with titles and descriptions of randomly selected 400 occupations from NCO (2015a) text manual. Then, I created prompt so that the model generates telework scores $\in [0, 1]$

for each 8-digit occupation. Details about the procedure are in Appendix B.5.1. 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 13 in the Appendix.

Table 36 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 physical-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.

Constructing Broad Occupation-Level Telework Potential. 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. Figure 6 depicts positive relationship between telework scores and weekly average income at occupation level. About 32% of Indian occupations with high telework potential account for 40% of all weekly average income. I then define a 3-digit occupation as teleworkable if this share exceeds 50th percentile value (0.62) for my main specification. That is,

$$T_o = \mathbb{1}\left(p_o > 0.475\right), \tag{18}$$

$$T_k = \mathbb{1}\left(\frac{1}{N_k}\sum_{o\in k} T_o > 50^{th}\text{percentile}\right) \tag{19}$$

where, T_o is a binary indicator for whether 8-digit occupation o is teleworkable, and p_o is its predicted telework score; N_k is the number of 8-digit occupations within 3-digit occupation k.

District-level Telework Shares

$$TWO_d = \frac{1}{N_d}\sum_{k\in d} T_k \tag{20}$$

where TWO_d is the district-level shares of teleworkable occupations, N_d is the total number of 3-digit occupations observed in district d, and T_k is share of 3-digit teleworkable occupations k. This time-invariant measure is computed by pooling the pre-COVID period PLFS rounds of 2017–18 and 2018–19. Figure 7 shows the districtwise distribution of TWO_d.

Digital Infrastructure

The second component of telework exposure is digital infrastructure. Using raw data from OpenCelliD, I measure district-level connectivity using the density of cell towers per square kilometer of district land area. Tower density is log-transformed to account for diminishing marginal returns to additional towers in already well-connected districts:

$$\text{Tower}_{dt} = \ln\left(\frac{\text{Towers}_{dt}}{\text{Area}_d}\right) \tag{21}$$

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 three years ($\text{Tower}_{d,t-3}$) for two reasons. First, it addresses reverse causality concerns: tower placement decisions are made years in advance of deployment and reflect prior assessments of infrastructure demand rather than contemporaneous labor market conditions. Second, a three-year lag accounts for the technology adoption lag between tower construction and utilization by population. Newly constructed towers take time to be adopted by local households and businesses.

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:

$$\text{Exposure}_{dt} = TWO_d \times \text{Tower}_{d,t-3} \tag{22}$$

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.

4 Methods

4.1 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 & Restrepo, 2020; Hjort & Poulsen, 2019). The empirical strategy leverages temporal within-district variation in telework exposure while accounting for time-invariant district characteristics and time-varying year fixed effects.

4.2 Baseline Specification

My baseline specification estimates the relationship between telework exposure and a woman's paid labor force participation using a two-way fixed effects (TWFE) model:

$$Y_{idt} = \alpha + \beta \cdot \text{Exposure}_{dt} + X'_{it}\gamma + \delta_d + \delta_t + \varepsilon_{idt} \tag{23}$$

where Y_{idt} is a dummy if woman-i participates in labor market. X_{it} includes age, education level, marital status, religion, and social group. District and year fixed effects are included, and standard errors are clustered at the district level. The sample is restricted to those aged above 18 years because adolescents (aged 14–18 years) cannot be employed in hazardous occupations, such as mines, factories, or industries involving chemicals. Standard errors are clustered at the district level to account for serial correlation in outcomes within districts over time.

4.3 Extended Specification with time-varying district-level and state-level controls

One potential concern is that changes in cell tower density could be correlated with development trends in a district that also influence women's labor supply. For example, districts experiencing faster growth in urbanization, public investment and business may receive more telecom infrastructure. To address this concern, I extend the baseline model with log of district-level nighttime lights lagged by three years as following

$$Y_{idt} = \alpha + \beta \cdot \text{Exposure}_{dt} + X'_{it}\gamma + \lambda N_{d,t-3} + \delta_d + \delta_t + \varphi_{idt} \tag{24}$$

where $N_{d,t-3}$ absorbs variation in district-level development. I use lagged rather than contemporaneous values to avoid reverse causality contemporaneous variable may lead to reverse causality. Several studies have used nighttime lights as proxy for development outcomes (e.g.,Alesina et al., 2016). This helps to isolate effects of telework exposure from confounding development trends.

Moreover, several Indian states have introduced cash transfer programs targeted at women including 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*. Since these programs target women's household income, it may directly affect women's decisions to participate in paid work. To account for these, I include state-by-year fixed effects (τ_{st}), which absorb all time-varying state-level shocks. The specification is as follows:

$$Y_{idt} = \alpha + \beta \cdot \text{Exposure}_{dt} + X'_{it}\gamma + \lambda N_{d,t-3} + \delta_d + \delta_t + \tau_{st} + \varphi_{idt} \tag{25}$$

4.4 First Stage Validation: Workplace Location and Telework Exposure

A fundamental concern in interpreting telework exposure is whether it captures meaningful variation in flexible work arrangements. Using reported location of workplace under principal activity[2] status, I examine if districts with higher telework exposure are also characterized

[2] i.e., over the last 365 days

by work arrangements whose usual workplace location are remote or flexible.

It is important to note that the workplace location does not directly identify telework. It may also include informal home-based production and unpaid family worker. Hence, I construct three indicators: first, I define a broad flexible location dummy which takes value 1 if the respondent reports working from own dwelling unit, a structure attached to the dwelling, an open area adjacent to the dwelling, a detached structure adjacent to the dwelling, or reports having no fixed workplace. Second, I define an urban broad flexible-location indicator using urban own-dwelling, adjacent-locations, and no fixed workplace. Third, I define a stricter urban flexible-location indicator equal to one if the respondent reports working from her own dwelling unit in an urban area or reports having no fixed workplace.

This estimation provides a measurement-validation check: if the constructed exposure measure captures meaningful variation in flexible work opportunities, it should be positively associated with the probability that a respondent's principal workplace is located at home, near home, or has no fixed location. Thus, the specification is:

$$\text{Flexible Location}_{idt} = \beta \text{Exposure}_{dt} + X'_{idt}\gamma + \phi N_{d,t-3} + \delta_d + \lambda_t + \theta_{st} + \varepsilon_{idt}. \tag{26}$$

where β is the coefficient of interest. The vector X_{idt} includes age, education, marital status, religion, social group. $N_{d,t-3}$ measure lagged nightlights. δ_d λ_t, and θ_{st} respectively denote district, year and state-year fixed effects. Standard errors are clustered at the district level. Because the outcome is based only on reported workplace location and does not use the occupation-based teleworkability measure, this exercise avoids mechanically validating the exposure measure with one of its own components.

5 Results

5.1 Validation Results

Table 4 reports validation estimates using flexible workplace location under principal activity status as the outcome. Column (1) captures broad definition of flexible workplace location. Columns (2)–(3) restrict on flexible workplace locations in urban areas. Such restriction reduces concerns that the first measurement captures agricultural labor where individuals may work near or around their own dwelling unit. Column (3)uses stricter definition urban flexible workplace location as it captures only those who work from home or those who has no fixed workplace.

The results show that telework exposure is positively associated with flexible-location work across all three definitions. In column (1), a one-standard-deviation increase in telework exposure is associated with a 0.51 percentage point increase in the probability that the respondent's principal workplace is in a broad flexible location. When the outcome is concentrated only in urban areas, the estimated relationship continues to remain positive.

A one-standard-deviation increase in telework exposure is associated with 0.40 percentage point increase in the probability of working in flexible locations in urban areas and 0.29 percentage point increase in working from home and/or flexible workplace (Columns (2)–(3), Table 4).
These results suggest that the telework exposure measure captures meaningful variation in spatially flexible work arrangements. The estimates are especially precise for the urban definitions, which is consistent with the idea that digitally enabled flexible work is more likely to be reflected in urban workplace locations. Because the location variable refers to principal activity status over the past 365 days, the results indicate that high-exposure districts are characterized by more flexible usual workplace arrangements, rather than as direct evidence of contemporaneous remote work adoption.

5.2 Key Results

Exposure to telework potential substantially increases female labor supply. Table 5 presents estimates of telework exposure effects on female labor supply across specifications. The baseline specification (Column 1) shows that a one-standard-deviation increase above the median raises female labor force participation by 2.01 percentage points. The effect remains stable as more controls are gradually added: 1.96 percentage points with lagged nightlights (Column 2), 1.6 percentage points with state-by-year fixed effects (Column 3), and 1.7 percentage points in the full specification (Column 4). Thus, the estimates remain consistent across specifications.

Figure 9 visualizes the underlying relationship by plotting predicted female labor force participation using both continuous and binned telework work exposure. Panel 9a confirms a positive, monotonically increasing gradient—the predicted participation rate rises from about 21% at the lowest exposure levels to around 34% at the highest. Panel 9b corroborates this pattern without imposing linearity. It shows that the overall relationship is positive but it is not monotonically increasing. Predicted female labor supply rises steeply when telework exposure rises from less than 1 percentile to 10–25 percentile bins. Beyond this, the relationship becomes considerably flatter during 10–25 percentile and 25–50 percentile bins of exposure. This is followed by modest dip around 50–75 percentiles. Thereafter, the predicted female labor force participation rises steadily beyond 75$^{\text{th}}$ percentile of exposure which includes districts such as Northwest Delhi, Chennai, Bangalore, Pune, Thane. Districts in the lowest exposure ($\leq$ 25th percentile) are Ahmedabad, Nadia, Jaipur, Murshidabad, Nagpur, Chittoor. The distribution of districts are depicted in figure 11.

The magnitude of these effects is economically significant. The preferred estimate in column (4) implies that a one-standard-deviation increase in telework exposure raises female paid labor force participation by 1.7 percentage points. Given a sample mean participation rate of 28.7 percent, this represents a 5.9 percent increase relative to the mean. These results suggest that districts with higher exposure to telework potential experience higher female labor force participation. These findings contribute to recent growing evidence on the nexus between flexible and remote work arrangements and women's paid labor: Bloom et al. (2024) showed that hybrid work arrangements reduced female employees' quit rates by one-third. Harrington and Kahn (2025) find that expansion of remote work increased mother's employment by 0.78 percentage points relative to other women. Banerjee et al. (2025) found that freelancing jobs with flexible working hours attracted women's applications roughly twice as much as those of men's. In a randomized experiment with 1,670 households in West Bengal, India, Ho et al. (2024) showed that work-from-home jobs more than triples employment among women.

5.3 Robustness Check

5.3.1 Falsification Tests

Table 6 reports a set of falsification tests using placebo outcomes. These help to assess whether the baseline estimates reflect broader district-level labor supply or local development trends.

Columns (1)–(2) show the results for men's labor supply and underage individual's labor supply. Telework exposure has no statistically significant effect on participation of men aged 18–49 years because general improvements in local labor demand should also influence men in their prime working age (column (1), Table 6). Similarly, telework has negligible effect on underage individual's paid labor force participation (column (2), Table 6) Thus, absence of corresponding effects on men and underage individuals indicate that the baseline estimates are less likely to be driven by broad employment trends in a district. I also examine whether the telework exposure is associated with local level development. A one-standard-deviation increase in telework exposure raises bank branch density by 5.3% but it is not statistically significant (column (3), Table 6). Similarly, telework exposure has marginal and insignificant effect on economic growth (column (4), Table 6). Thus, the key results are not simply capturing broad development trends.

Hence, these placebo results indicate that the main results are not simply capturing broad district-level development trends.

5.3.2 Sensitivity Analyses

Alternative Thresholds. A potential concern is that the estimated effects of telework exposure could be sensitive to the cutoff used to aggregate 8-digit specific teleworkable occupations into the 3-digit occupation groups observed in PLFS data. In the baseline specification, I classify a 3-digit occupation as teleworkable if its share of teleworkable 8-digit occupations is above the median across 3-digit occupations. Table 7 shows that the results are robust to alternative athresholds for defining teleworkability at the 3-digit occupation level. Column (1) does not impose an additional threshold at the 3-digit level. Instead, it uses the continuous share of teleworkable 8-digit occupations within each 3-digit occupation. Columns (2)–(6) impose alternative cutoffs, using the 10th, 25th, 30th, 75th, and 90th percentiles of the 3-digit teleworkability-share distribution. The estimated effects remain positive and statistically significant across all definitions. Across specifications, a one-standard-deviation increase in telework exposure raises female paid labor force participation by 1.4–1.8 percentage points. These estimates suggest that the baseline results are not driven by the particular threshold used to translate telework predictions from detailed 8-digit occupation into the 3-digit PLFS occupation. Rather, the positive effect of telework exposure is robust to both continuous and threshold-based measures of teleworkability.

District-Representativeness. A second potential concern lies with sampling design of the PLFS database. It is not designed to be representative at the district level. Some districts consist of relatively few first stage units (FSUs) in certain survey rounds. This raises a concern that the baseline results may be shaped by sparsely sampled or noisy district by year observations. To address this, I, first, restrict the sample to district-round cells that meet stricter minimum FSU coverage thresholds. The results are shown in Table 8. As the minimum FSU threshold gradually increases from 1% to 25%, the effect of telework exposure ranges between 1.67 to 2.03 percentage points which remains close to the baseline estimate. Thus, the pattern suggests that the estimated coefficients are not spurious and are not driven by thinly sampled district-year cells. Excluding noisier district-year observations, rather, generates slightly larger estimates which implies that the sampling noise could attenuate the estimated effect instead of the nexus between telework exposure and female labor supply. Following Peters et al. (2025), next, I restrict my sample only to those districts with at least 50 observations in each year which reduces the number of districts from 624 to 606. The estimates remain robust and similar to the baseline results (Table 9).

5.3.3 Alternative Specifications

Alternative Outcome Variable. I examine whether telework exposure affects intensive margin of female labor supply. Instead of participation dummy, I replace the dependent variable with log transformation of weekly working hours. Table 10 shows that a one-standard-deviation increase in telework exposure increases women's working hours by 5.6% per week (Column 4, Table 10).

Alternative Exposure measurement. I test whether the results are robust to using 4G mobile-tower density instead of overall cell-tower density.I reconstruct the exposure index by interacting baseline district-level teleworkability with lagged 4G mobile-tower density:

$$\text{Exposure}_{dt}^{4G} = TWO_d \times \text{Tower}_{d,t-3}^{4G}. \tag{27}$$

This preserves the logic of baseline exposure measure in while using high-speed mobile internet access. Using the three-year lag maintains the consistency with the baseline structure. Table 11 shows that the results remain consistent with baseline results. A one-standard-deviation increase in telework exposure raises female labor supply by 0.64–0.76 percentage points across all specifications as fixed effects and controls are gradually added. Thus, the results remain robust to measuring digital connectivity using 4G-specific cell-tower density instead of overall cell-towers.

Event Study Analysis. I complement the baseline analysis with a staggered event-study design based on the timing of improvements in district-level 4G connectivity. I define a district's event year as the first year in which its 4G connectivity crosses the 75th percentile threshold. Districts that never cross this threshold during the sample period serve as the comparison group. I then estimate dynamic effects separately for districts with high and low baseline teleworkability, defined using the median district share of teleworkable occupations during 2017–2019. This allows me to examine whether improvements in digital connectivity are followed by larger changes in women's paid labor supply in districts where the occupational structure is more compatible with telework. Since local occupational composition changes slowly over time, the short-run variation in telework exposure in this framework is driven mainly by improvements in 4G connectivity rather than by changes in teleworkable occupation shares. The event study specification is:

$$Y_{idt} = \sum_{k \neq -1} \beta_k \left(\mathbf{1}\{t - T_d = k\} \right) + \gamma X_{idt} + \delta_d + \lambda_t + \varepsilon_{idt} \tag{28}$$

where Y_{idt} denotes paid labor supply for woman i in district d and year t. T_d is the first year in which district d crosses the 75th percentile of 4G connectivity. The indicator $\mathbf{1}\{t-T_d = k\}$ denotes event time relative to this first crossing, with $k = -1$ omitted as the reference period. The vector X_{idt} includes individual-level controls and lagged nightlights. District fixed effects are denoted by δ_d, while λ_{st} denotes state-by-year fixed effects. I estimate this specification separately for districts above and below the median baseline teleworkable occupation share, measured using the 2017–2019 district occupational composition.

Figure 10 examines the dynamic evolution of these effects using the Sun and Abraham (2021) heterogeneity robust estimator. Panel (a) reveals no differential pre-trend since the coefficients are statistically insignificant in districts with high baseline teleworkability. Once each district crosses the threshold of 50^{th} percentile 4G cell towers, trends in female labor force participation grow over time, reaching 4.4 percentage points by next two years ($t = 2$). Panel (b) similarly shows no differential pre-trend in districts with low baseline teleworkability. However, female labor supply does not significantly change in these districts after they exceed median threshold of 4G connectivity. The absence of pre-trend indicates that the results are not driven by pre-existing differences in female labor supply. The limitation is that there is only two pre-trend period points, with $t = -1$ being used as reference period. More importantly, if expansion of 4G internet proxies for broader development of a district, female labor supply should increase after connectivity improvements irrespective of the district's shares of teleworkable occupations. Instead, the effect emerges only in districts where the occupation composition is more compatible with remote or flexible work. This suggests that the impact of digital infrastructure operates through telework-relevant occupational composition, rather than through connectivity expansion alone.

5.4 Heterogeneous Effects

The baseline telework exposure effects mask important heterogeneity across population subgroups. 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.

5.4.1 Social norms

Marital Status. Table 12 shows that the effects are concentrated among married women. A one-standard-deviation increase in telework exposure raises paid labor force participation among married women by 1.95 percentage points (Column 1b, Table 12). In contrast, the corresponding estimate for unmarried women is small, and statistically insignificant (Columns 2a–2b, Table 12). Thus, telework exposure appears to have a larger effect on married women who experience tighter norms around home production. This pattern is consistent with existing studies which argue that flexible or remote-compatible work unlocks married women's paid labor supply (Ho et al., 2024; Jalota & Ho, 2024).

Husband's occupation. Table 13 shows that the effects of telework exposure are concentrated among women whose husbands are employed in non-teleworkable occupations. A one-standard-deviation increase in telework exposure raises paid labor force participation among these women by 2.69 percentage points (Column 1b, Table 13). In contrast, women's participation does not significantly respond to telework exposure when their husbands are employed in teleworkable occupations (Columns 2a–2b, Table 13). Table 14 shows that this pattern is not driven only by broad differences in husbands' employment type. Among women whose husbands hold regular-salaried jobs, the effect remains positive when the husband's occupation is low-teleworkable, but is close to zero and statistically insignificant when the husband's occupation is high-teleworkable. A similar pattern appears among women whose husbands are self-employed: the effect is large and statistically significant when the husband's occupation is low-teleworkable, but small and insignificant when the husband's occupation is high-teleworkable. These additional evidence captures whether his work provides a flexible adjustment margin. Thus, telework exposure appears to have a larger effect when the husbands are in less flexible jobs. This finding has implications for the literature on co-location frictions[3] in dual-earner households. Studies have shown that these constraints tend to reduce women's labor market gains since cuples are far more likely to move when it benefits husband's career (Foerster & Ulbricht, 2025; Yan, 2025). Remote or hybrid work relaxes this constraint by converting some outside opportunities into jobs that can be performed without relocation or a separate commute.

[3] When one spouse's job is location-bound, the household must coordinate job opportunities based on shared residential location

Household economic status Previous studies have shown that higher household income is correlated with lower female labor force participation (Klasen, 2019; Klasen et al., 2020). In poor households, women's participation is often high to alleviate financial distress, while paid work tend to rise among women in more affluent families with access to better quality jobs (Deshpande and Kabeer, 2024; Klasen and Pieters, 2015; Sarkar et al., 2019). Thus, household economic status may influence the nexus between telework exposure and female labor supply.

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 (Carver and Grimes, 2019; Deaton, 2016; Meyer and Sullivan, 2003). 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.

I find that a one-standard-deviation increase in telework exposure raises female labor force participation by nearly 1.9 percentage points among households with above-median MPCE (Columns (1)–(2), Table 16). On the contrary, the effect is negligible for women dwelling in households with below-median MPCE (Columns (3)–(4), Table 16). This indicates that the effect of telework exposure on women's paid labor varies by household economic resources. If a women belong to households with higher economic status, they are more exposed to telework-compatible occupations and internet connectivity. In case of poor households, however, lack of complementary resources such as higher education, digital devices constrain women from taking advantage of flexible-job opportunities.

Crime and mobility constraints. Studies have shown that rise in crimes against increases non-pecuniary costs of traveling to work (Chakraborty et al., 2018). This, in turn, reduce women's paid labor supply (Chakraborty et al., 2018; Siddique, 2022). If mobility constraints are reduced by improving transport facilities, women's labor supply improves greatly (Field and Vyborny, 2022; Martinez et al.,2018). Because reported crimes against women influence their free physical mobility, I utilize district-level reported crimes against women as a proxy for mobility constraints by classifying the districts above or below the national median value. Table 17 shows that the effect of telework exposure on women's paid labor is concentrated in districts with above-median reported crimes. A one-standard-deviation rise in telework exposure increases female labor supply by 1.9–2.23 percentage points (Columns (1)–(4), Table 17). On the contrary, the effect of telework exposure is insignificant on women's participation if they are dwelling in districts with less-than-median reported crimes against women. These suggest that telework exposure may relax mobility constraints for women. In areas with higher crimes against women, non-pecuniary cost of working outside (e.g., commuting and social stigma of traveling alone) are likely to be very high and hence flexible work arrangements can raise women's labor supply. In districts with low incidence of violence against women, telework exposure does not play significant role. Hence, high telework potential has larger labor supply effects where physical mobility is more binding.

5.4.2 Care burden

Dependency ratio. According to UNCTAD (2026), dependency ratio refers to the number of children and older persons to the working-age population. I classify a household as high dependency if its dependency ratio exceeds the median value of the dependency-ratio distribution. Table 18 examines heterogeneity by household dependency. While the effects are statistically significant for both high- and low-dependency households,the magnitude is larger among women in households with higher dependency ratio. In the full specification, a one-standard-deviation increase in telework exposure raises participation by 1.87 percentage points for women in high-dependency households, which is 0.35 percentage point more than those in low-dependency households (Columns 1b and 2b, Table 18). This pattern indicates that telework exposure is likely to be more valuable for those with more salient household care responsibilities. At the same time, the positive effect among low-dependency households indicates that the mechanism is not limited only to care constraints.

Presence of children by various age groups. Table 19 examines whether the effect of telework exposure varies by the age of children in the household. The estimates show that the response is concentrated among married women with younger children. A one-standard-deviation increase in telework exposure raises female labor force participation by 1.70 percentage points among married women living in households with children under age five (Column 1, Table 19), and by 1.57 percentage points among married women dwelling in households with children aged 5–10 years (Column 2, Table 19). The corresponding estimates for women in households with children aged 11 years and above are smaller and statistically insignificant (Columns 3-4, Table 19). This pattern shows that telework exposure relaxes childcare constraints most strongly when children are young and require more intensive care. These results are consistent with recent evidence that remote work opportunities are likely to reduce motherhood penalty (Arntz et al., 2022; D'Angelis & Horn, 2026; Dettling, 2016b; Harrington & Kahn, 2025; Song, 2025).

5.4.3 Job contracts

Table 20 examines whether the labor-supply response to telework exposure differs by the formality of women's jobs, measured by whether the job includes a written contract. The estimates suggest that telework exposure is more closely associated with entry into contracted work than with non-contracted work. In the specification with demographic controls, a one-standard-deviation increase in telework exposure raises the probability of paid work with a job contract by 1.03 percentage points (Column 1b, Table 20). By contrast, the corresponding estimate for paid work without a job contract is close to zero and statistically insignificant (Columns 2a–2b, Table 20).

This pattern suggests that the effect of telework exposure is not driven only by entry into informal or low-quality work. Instead, telework-compatible labor markets may expand access to more formal forms of paid employment. The estimate for contracted work is only marginally significant, so I interpret this result cautiously; nevertheless, it is consistent with telework exposure improving not only the extensive margin of women's paid work, but also the type of jobs into which women enter.

5.4.4 Human capital & stages of life cycle

Technical education. Table 21 examines whether the effect of telework exposure differs by technical education among college-educated women. The results show a sharp difference between women with technical and non-technical degrees. Among college-educated women without technical degrees, the estimated effect of telework exposure is close to zero and statistically insignificant. In contrast, among women with technical degrees, a one-standard-deviation increase in telework exposure raises paid labor force participation by 4.75 percentage points in the specification with controls (Column 2b, Table 21).

This pattern is consistent with telework exposure being most valuable for women whose human capital is better matched to remote-compatible or technology-enabled jobs. Technical education may increase women's ability to take advantage of expanding digital infrastructure because such skills are more easily deployed in occupations that can be performed remotely or with greater workplace flexibility. However, it should be noted that the sample of women with technical degrees is relatively smaller than those with non-technical college degrees.

Age heterogeneity. Table 22 shows that the effect of telework exposure varies across the life cycle. The estimated effect is small and statistically insignificant among younger women aged 19–24. In contrast, the effect is positive and statistically significant among women aged 25–49 and 50–75. A one-standard-deviation increase in telework exposure raises paid labor force participation by 1.77 percentage points among women aged 25–49 and by 2.03 percentage points among women aged 50–75.

These results suggest that telework exposure is most consequential for women who are more likely to be at stages of the life cycle where paid work decisions interact with household responsibilities, marriage, childcare, or re-entry into employment. The insignificant effect among women aged 19–24 may be due to continued education or lower exposure to household constraints that make flexibility especially valuable. The positive effects among prime-age and older women are consistent with telework exposure relaxing mobility, commuting, and household-production constraints for women with stronger potential attachment to paid work.

5.5 Mechanisms: Labor-side

This section examines potential mechanisms through which telework exposure increases women's paid labor supply. The theoretical framework suggests that telework may affect labor supply through two related channels. First, it may increase the returns to work or improve access to income-generating opportunities. Second, it may reduce the time and household-production constraints that keep women primarily engaged in unpaid domestic work.

Monthly earnings. I first examine whether telework exposure increases women's monthly earnings. The dependent variable is measured as log(1 + monthly income), where monthly income includes wage earnings, regular wage earnings, and self-employment earnings. The log transformation retains women with zero earnings, which is important because many women in the sample are outside the labor force.

Table 23 shows that telework exposure is positively associated with women's monthly income. Across specifications, a one-standard-deviation increase in telework exposure is associated with a 10.8–10.9 percent increase in monthly income. Since the dependent variable includes zeros, this estimate should be interpreted as reflecting both extensive-margin entry into paid work and intensive-margin increases in earnings among women who are already working. This result complements the baseline participation estimates by showing that telework exposure is associated not only with a higher probability of paid work, but also with greater income from work.

Unpaid household labor. I next examine whether telework exposure reduces women's unpaid household labor. The dependent variable is an indicator equal to one if unpaid household labor is reported as the woman's primary activity and zero otherwise. This outcome captures whether women remain primarily engaged in domestic responsibilities rather than market work.

Table 24 shows that telework exposure is negatively associated with unpaid household labor. In the preferred specification, a one-standard-deviation increase in telework exposure reduces the probability that unpaid household labor is a woman's primary activity by 1.39 percentage points. Relative to the mean of 0.635, this corresponds to a 2.2 percent decline.

This pattern supports the interpretation that telework exposure relaxes constraints that keep women primarily engaged in unpaid domestic work. If flexible or digitally enabled work reduces commuting costs, safety concerns, or the fixed time costs of market work, women may be better able to reallocate time from unpaid household production toward paid employment. The result is therefore consistent with a time-allocation channel: telework exposure appears to reduce the likelihood that women remain outside the labor market because of domestic responsibilities.

6 Cheap 4G Internet Expansion, Telework Exposure, and Female Labor Supply

The baseline results show that districts with more telework exposure witness increase in women's paid labor supply. A remaining concern, however, is that districts with faster growth in internet connectivity may differ from other districts in ways that are not fully captured by observed controls. To address this concern, I exploit the rapid national expansion of cheap 4G internet following the entry of internet service provider, Reliance Jio as a source of exogeneous variation in digital connectivity. I combine this national 4G expansion with my pre-determined district-level shares of teleworkable occupations to construct a shift-share instrument for telework exposure.

6.1 Background: Reliance Jio and the Expansion of Cheap 4G Internet

In late 2016, Reliance Jio disrupted the Indian telecommunications market by offering free voice calls, SMS, and high-speed 4G LTE data during its introductory period. This expansion sharply reduced the price of mobile data and accelerated the diffusion of internet use across India. Data prices fell from USD 2.78 per gigabyte in 2016 to USD 0.23 in 2017, representing a decline of approximately 93 percent. The timing and scale of this national shock created a rapid expansion in affordable digital connectivity that was not targeted specifically toward districts with higher potential for female employment.

This setting is useful for identifying the labor-market effects of telework exposure because the national expansion of cheap 4G internet should matter more in districts whose occupational structure was already more compatible with telework. In districts with a larger predetermined share of teleworkable occupations, improvements in digital connectivity are more likely to translate into feasible remote or flexible work opportunities. In contrast, districts with low baseline teleworkability may experience the same aggregate internet shock but have fewer occupations through which digital connectivity can relax workplace-location constraints. This motivates the shift-share design.

6.2 Shift-Share Instrument

I construct a shift-share instrument using two components: a time-invariant district's shares of teleworkable occupations and a national time-varying shifter. The national shifter is the growth in 4G connectivity across NFHS survey rounds. Specifically, the instrument is defined as

$$Z_{dr} = TWO_d \times \Delta 4G_r, \tag{29}$$

where TWO_d denotes the district's time-invariant baseline teleworkability share, and $\Delta 4G_r$ denotes national 4G growth in survey round (r). The identifying variation comes from the fact that the nationwide expansion in cheap 4G internet has different effects across districts depending on their pre-existing occupational capacity for telework.

The endogenous variable is district-level telework exposure, constructed as the interaction between baseline teleworkability and lagged district-level digital infrastructure:

$$\text{Exposure}_{dr} = TWO_d \times \ln(\text{TowerDensity}_{d,r-3}), \tag{30}$$

where $\text{TowerDensity}_{d,r-3}$ is lagged district-level tower density. In the NFHS analysis, the lagged tower year is 2012 for NFHS-4 and 2016 for NFHS-5. The use of lagged infrastructure reduces simultaneity concerns and ensures that the measured exposure predates the labor-market outcome.

6.3 Empirical Specification

I estimate two-stage least squares specifications using NFHS data. The second-stage equation is

$$y_{idr} = \beta \widehat{\text{Exposure}}_{dr} + \Gamma' W_{idr} + \alpha_d + \delta_r + \varepsilon_{idr}, \tag{31}$$

where y_{idr} is a labor-market outcome for woman (i) in district (d) and survey round (r). The main outcome equals one if the woman is engaged in non-agricultural labor and zero if she is out of the workforce; agricultural workers are excluded from this estimation sample. W_{idr} includes individual controls for age, caste or tribe, education, and marital status. District fixed effects, α_d, absorb time-invariant district characteristics, while survey-round fixed effects, δ_r, absorb aggregate changes common to all districts. Standard errors are clustered at the district level.

The first-stage equation is

$$\text{Exposure}_{dr} = \pi Z_{dr} + \Lambda' W_{idr} + \alpha_d + \delta_r + \nu_{idr}. \tag{32}$$

The coefficient π captures whether districts with higher baseline teleworkability experienced larger increases in telework exposure when national 4G connectivity expanded. The corresponding reduced-form specification is

$$y_{idr} = \rho Z_{dr} + \Phi' W_{idr} + \alpha_d + \delta_r + u_{idr}. \tag{33}$$

The reduced-form coefficient ρ estimates whether the interaction between predetermined teleworkability and national 4G expansion directly predicts women's movement into non-agricultural work.

6.4 Results

Table 26 reports the instrumental-variable estimates. Panel A presents the second-stage results. It shows that a one-standard-deviation increase in the instrumented telework exposure raises female labor force participation by 3.68–3.9 percentage points (Columns (1) and (2)). Given the mean participation is 0.177, the estimated coefficient approximately accounts for 20.7% of women's labor supply. This suggests that telework exposure shifts more women into non-agricultural employment.Panel B provides the first-stage estimates. The Bartik instrument is a strong predictor of exposure—the coefficient is 0.481 (s.e. = 0.033) and the Kleibergen–Paap F-statistic is 216.5—well above conventional thresholds for weak-instrument bias.

Panel C gives the estimates for reduced-form specification (33). It shows that one-standard-deviation increase in instrumental exposure raises women's paid labor supply by 1.77 percentage points (Column (2)). This reduced-form relationship is important because it shows that the source of instrumented variation itself predicts women's labor-market outcomes in the expected direction.

Note that the table also reports endogeneity diagnostics. The Durbin and Wu-Hausman tests reject the null that telework exposure can be treated as exogenous, and the Wooldridge score test similarly rejects exogeneity. These tests support the use of the instrumental-variable specification. Since the model includes one endogenous regressor and one excluded instrument, it is exactly identified; therefore, overidentification tests are not available.

6.5 Mechanisms: Digital Accessibility & Mobility

The estimated relationship between shift-share instrument and women's participation in paid labor raise questions about underlying pathways. This section examines three mechanisms through which the shift-share telework exposure can influence female labor supply.

Internet Access. The instrumental telework exposure can influence female labor supply through presence of digital connectivity. If a woman resides in a household with internet, she is more likely to have access to information, communication and technological support needed to search for flexible jobs or work remotely when hybrid arrangements are feasible. To capture this, I use the variable on internet access at household level[4]. Table 27 shows the result for household internet access. A one-standard-deviation increase in the instrument telework exposure raises household's internet access by 2.14 percentage points (Column (2)).

Computer Access. The relationship between telework exposure and women's paid labor may also depend on availability of digital device, particularly computer without which flexible jobs are not 'flexible' enough. So, I use the variable on computer access at household level as a dependent variable [5]. Table 28 shows that a one-standard-deviation increase in the instrument telework exposure raises household's access to computer by 0.89 percentage points (Column (2)).

Freedom of Movement. In conservative society, female labor supply may be constrained when women's independent mobility is stigmatized and discouraged. The central idea is that flexible work arrangements reduce initial cost of labor-market entry and may graudally weaken mobility-related barriers. I measure this channel using a dummy variable that takes value 1 if a woman is allowed to go by herself to the market, health facility and outside the locality (town/village). Table 29 shows that a one-standard-deviation increase in instrument telework exposure increases women's freedom to move by 12.56 percentage points (Column (2)). This is consistent with Ho et al. (2024)'s evidence from randomized experiment in West Bengal, India which showed that initial home-based flexible jobs later encourgaed women to transition towards outside paid labor. Thus, freedom of movement not only serve as precondition to work but also expands as women gain labor-market exposure.

[4] Data on internet access at individual-level is available only in NFHS-5 which is the second round.

[5] Data on computer access at individual-level could be a better measure but it is available only in NFHS-5 which is the second round.

6.6 Identifying Conditions and Threats to Validity

The exclusion restriction requires that the instrument does not influence the outcome variable except through the endogenous independent variable. In this case, the shift-share instrument should affect women's participation in paid labor only through its effect on the district's telework exposure. Since the instrument is the interaction between district's baseline shares of teleworkable occupations and national 4G internet growth, the identifying assumption is not about 4G internet rollout alone. Rather, it is that national 4G expansion affects women's labor supply differently across districts only because districts differ in their baseline potential for telework. A violation of this assumption would arise if districts with higher baseline teleworkability were also on different unobserved trajectories—such as faster growth in local labor demand, urbanization, digital infrastructure, or female employment opportunities—that coincided with national 4G expansion and independently increased women's labor supply. The empirical strategy addresses part of this concern by absorbing time-invariant district characteristics through district fixed effects and common aggregate shocks through survey-round fixed effects.

6.7 Key Takeaways

The shift-share results reinforce the baseline findings. Districts with higher predetermined teleworkability experience larger increases in women's non-agricultural labor supply when national 4G connectivity expands. The IV estimates are larger than the baseline PLFS estimates, which is consistent with the instrument identifying variation among women whose employment decisions are more responsive to digitally enabled work opportunities. The first stage is strong, the reduced form is positive, and the mechanism results show corresponding improvements in household internet and computer access.

At the same time, the IV estimates should be interpreted as a local average treatment effect for the exogenous variation by cheap 4G expansion across districts with different baseline teleworkability. The results do not imply that internet expansion alone is sufficient to raise women's labor supply in all districts. Rather, they suggest that digital connectivity has larger labor-market effects where the local occupational structure already contains jobs that can plausibly be performed with greater flexibility. This distinction is important for policy: investments in digital infrastructure are likely to generate larger gains for women's employment when paired with labor-market institutions and firm practices that allow flexible or remote work.

7 Cost Benefit Analysis

In this section, I use my previous estimates from table 5 to quantify net benefits of 4G internet expansion by comparing annual women's earnings against infrastructure costs. I utilize standard welfare analysis methods used in development economics (Duflo and Pande, 2005; Vogel et al., 2024). The estimates should be interpreted as back-of-the-envelope welfare calculations instead of a full structural evaluations.

7.1 Method

Let B_d denotes annual earnings benefit in district d and C_d represents annualized cost of 4G internet expansion. Then, welfare gain in district d can be written as:

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

The corresponding benefit-cost ratio is

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

Using eq.(25), a one-standard-deviation-increase in telework exposure raises female labor force participation by 1.7 percentage points ($\hat{\beta} = 0.017$, $SE = 0.0053$). I translate this into annual district earnings gains using

$$B_d = \hat{\beta} \times N_d^F \times \bar{Y}_d^F, \tag{36}$$

where N_d^F is adult female population and $\bar{Y}_d^F$ is yearly average female earnings in district d.

On the cost side, I proxy 4G expansion by the increase in observed active 4G tower sites since 2017. Let ΔS_d denote this increase in district d. District capital cost is given by

$$K_d = \Delta S_d \times \kappa, \tag{37}$$

where κ is the official cost per added site. I quantify annual capital costs using

$$C_d = K_d \times \frac{r}{1 - (1 + r)^{-L}}, \tag{38}$$

with discount rate $r = 0.05$ and tower (asset) life $L = 10$. The preferred benchmark sets κ equal to the national 4G saturation cost of \$140,421 (which is INR 13.34 million) per site. However, the current cost estimates exclude OFC/backhaul, which can understate infrastructure costs.

7.2 Results

Table 30 reports the baseline welfare calculation. The main analysis sample contains 95 districts with non-missing annualized cost, and positive post-2017 tower additions. Aggregated annual earnings benefits amount to nearly \$2.31 million (Rs. 218,967.96 million)[6].

Using aggregate annualized costs of \$362.12 million (Rs. 34,374.19 million) under the baseline cost benchmark, this implies aggregate annual net benefits of \$1.945 billion (Rs. 184,593.77 million) and an aggregate benefit-cost ratio of 6.37. At the district level, the median benefit-cost ratio is 10.39, and 93.7 percent of districts in the main sample have

[6] using an exchange rate of INR 94.92496 per US dollar as of May 29, 2026

positive net benefits.

Robustness and Sensitivity Analysis. Table 31 reports robustness and sensitivity checks. In panel A, I assume that aggregate annual benefits remain unchanged while the per-site cost differs. The low-cost benchmark uses the 7,287-rural aspirational districts project[7] which implies a cost of \$0.083 million per site (INR. 7.88 millions per site). The mid-cost benchmark uses the 502-village project[8] which generates \$0.096 million per site (INR. 9.13 millions per site). The preferred benchmark, which is also the highest-cost case, uses the national 4G saturation project that gives \$0.141 million per site (INR. 13.34 millions per site). Aggregate benefit-cost ratios remain above one under all three benchmarks. In panel B, I report sensitivity analysis to the benefit side. First, I vary the estimated employment effect using the upper and lower bound of the 95% confidence interval (table 5). Based on the lower bound, the aggregate benefit-cost ratio exceeds one (2.48) and net benefits amount to \$0.53 billion (INR 50.79 billion). At the upper bound, the aggregate benefit-cost ratio rises to 10.26 and aggregate annual net benefits increase to \$3.35 billion (INR 318.40 billion). Second, I replace the preferred female earnings with a more conservative measure (bottom 10%). This lowers the aggregate benefit-cost ratio to 1.40 but it still remains above one. Following Duflo and Pande (2005), I apply a 15% deadweight loss of taxation markup to annualize the public cost. In this case, the benefit-cost ratio drops from 6.37 to 5.54 and aggregate net benefits is \$1.87 billion (Rs. 179.44 billion).

Hence, public investment in 4G internet expansion yields substantial earning gains among women. Every dollar spent in expanding 4G cell tower generates more than \$6 in annual earning benefits from telework induced rise in female labor force. These findings also have implications for market failures in providing digital infrastructure. If investments were made until marginal benefits from expansion equal marginal cost, many districts remain far from social benefits net of cost. Policies expanding affordable high-speed internet may improve women's labor market gains, especially if they respond to telework potential. This in turn can have long run implications for women's autonomy and agency.

8 Conclusion

This study is among the first few studies in emerging economies which provide causal evidence that telework exposure improves women's paid labor supply. A one-standard-deviation increase in telework exposure raises female paid labor force participation by 1.7 percentage points which accounts for 5.9% of the average female labor force participation in India. These results show that digitally enabled flexible work can increase women's employment in a setting where gender gaps in paid work remain large.

[7]Details available in https://usof.gov.in/en/7287-aspirational-villages

[8]Details available in https://usof.gov.in/en/502-uncovered-villages

Three findings stand out. First, the effects are concentrated among women for whom the constraints on office work are likely to be more binding. Telework exposure has larger effects among married women, women with young children, living in households with higher dependency burdens, residing in districts with higher reported gender-based violence, and whose husbands work in non-teleworkable occupations. These patterns are consistent with predictions from theoretical framework in which I show that a woman would choose to telework if it exceeds commuting costs and household production frictions. It reinforces that flexibility matters most when standard in-person jobs are costly to access.

Second, the mechanisms extend beyond simple employment entry. Telework exposure increases weekly working hours and monthly earnings, while reducing the probability that unpaid household labor is reported as a woman's primary activity. Moreover, telework exposure is associated with higher household internet access, greater computer access, and greater freedom of movement. These pathways suggest that telework exposure relaxes both digital and mobility constraints. By improving access to information, communication technologies, and flexible work opportunities, digital infrastructure can help women move from unpaid household production into paid labor.

Third, the cost-benefit analysis reports substantial net gains. Assuming a decade activity span for each tower site, 4G expansion generates \$2.31 billion in annual earnings benefits for women against \$0.36 billion in annualized infrastructure costs. This yields aggregate annual net benefits of \$1.94 billion and a benefit-cost ratio of 6.37. These estimates suggest that digital infrastructure can generate large social returns when it expands access to telework-compatible employment.

The evidence does not appear to reflect broad district-level development alone. Telework exposure does not significantly bank-branch density, or local economic growth. Validation exercises show that higher telework exposure is associated with flexible workplace locations, especially in urban areas where digitally enabled work is more plausible. Event-study estimates show that female labor force participation rises after improvements in 4G connectivity only in districts with high baseline shares of teleworkable occupations, while similar internet expansion does not generate significant response in districts with low shares. To strenghthen the causal interpretation, I use shift-share instrumented exposure where the '*shift*' is coming from nationwide 4G internet growth, followed by cheap internet scheme by an internet service provider while the '*share*' is measured by shares of teleworkable occupations.

The policy implication is not that internet expansion alone will close gender gaps in employment. Rather, the results suggest that digital infrastructure is most effective when paired with local labor-market conditions that allow remote or flexible work. Policies that expand affordable high-speed internet, improve women's access to digital devices and skills, and encourage firms to offer remote or hybrid jobs may generate larger employment gains than infrastructure investments alone. These policies may be especially valuable in contexts where women face mobility restrictions, childcare responsibilities, safety concerns, and social norms that make standard office work costly.

This study has three main limitations. The PLFS is nationally representative but not designed to be district-representative, so district-level exposure measures may be noisy. I address this concern through sample restrictions based on district-year coverage, but future research would benefit from more detailed district-level labor-market data. Second, the NFHS dataset does not contain detailed occupation description for each employed person as in case of PLFS. So, I map each district's baseline shares of teleworkable occupation from PLFS to NFHS, assuming that the occupation composition won't change much from 2015-16 to 2017-19 in each district. Finally, the cost estimates in the welfare analysis exclude OFC/backhaul costs and the benefit calculations do not capture non-pecuniary benefits such as autonomy, bargaining power, safety, or intergenerational gains.

The central lesson is that flexibility is produced jointly by local occupation composition and infrastructure. Digital connectivity matters most when it reaches places where the occupational structure contains tasks that can be performed remotely or flexibly. In this sense, telework exposure provides a demand-side channel through which digitalization can make structural transformation more inclusive for women.

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Figures

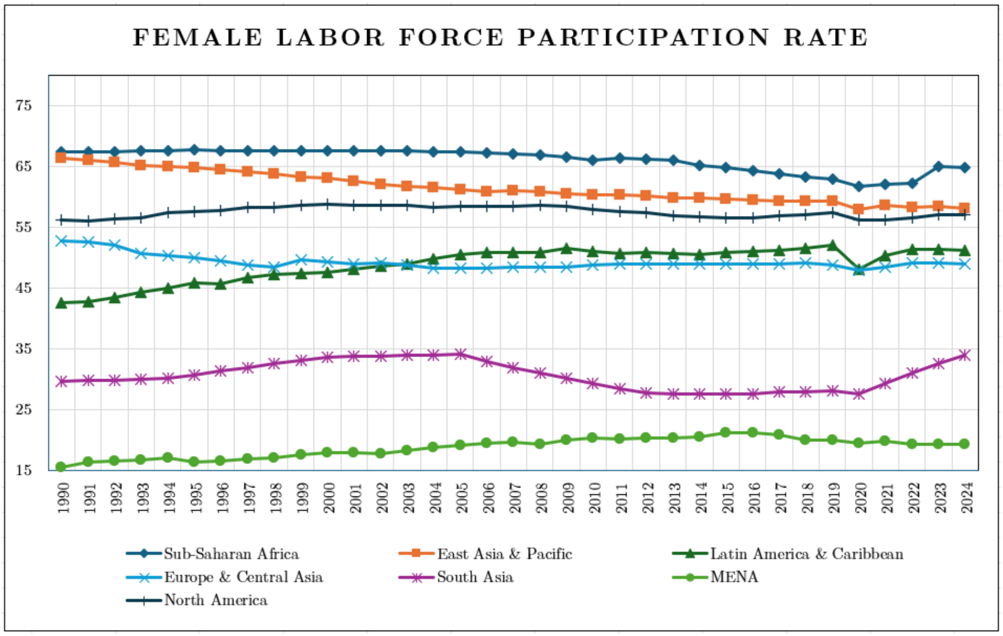


Figure 1: Trends in FLFP by region over three decades.

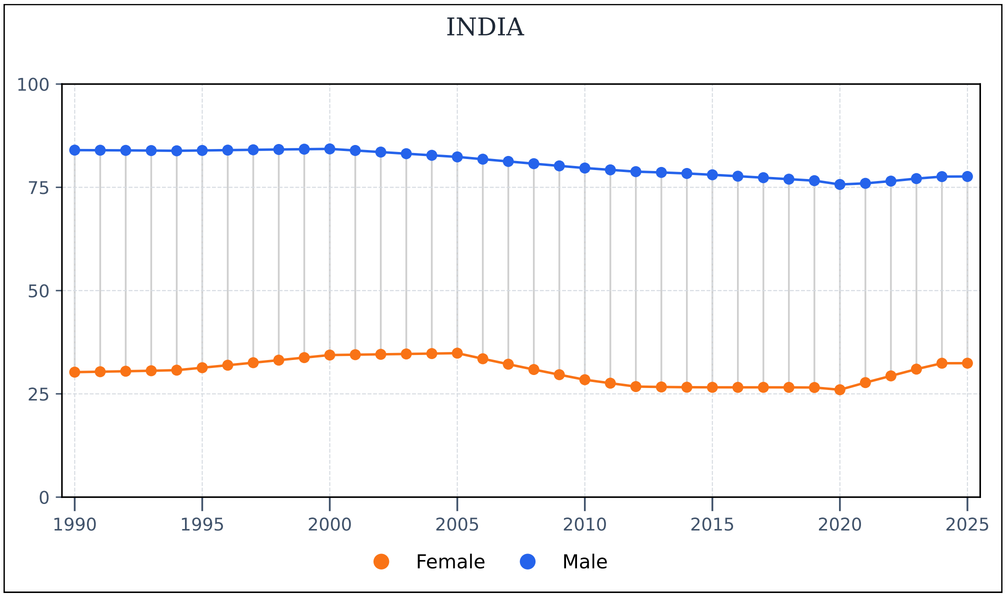
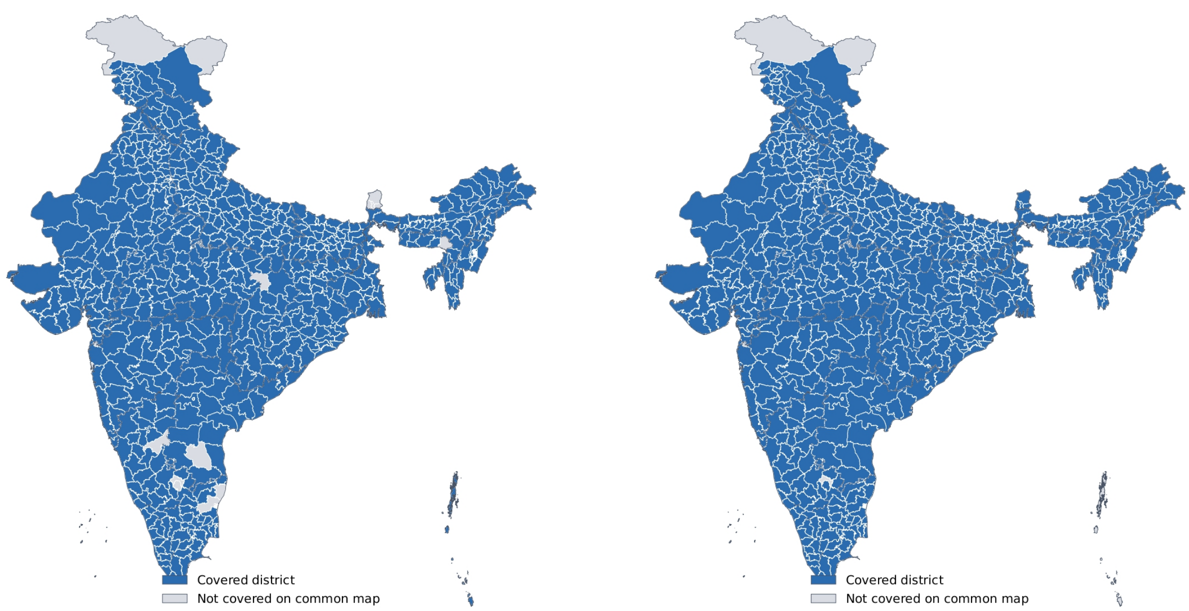


Figure 2: Gender Inequality in Paid Labor Force Participation in India.



(a) PLFS (625 districts)

(b) NFHS (632 districts)

Figure 3: Notes: Map of the availability of districts by dataset. Available districts are colored in blue. Panel 1a displays districts surveyed in all seven rounds of PLFS. Panel 1b shows districts in both rounds of NFHS data.

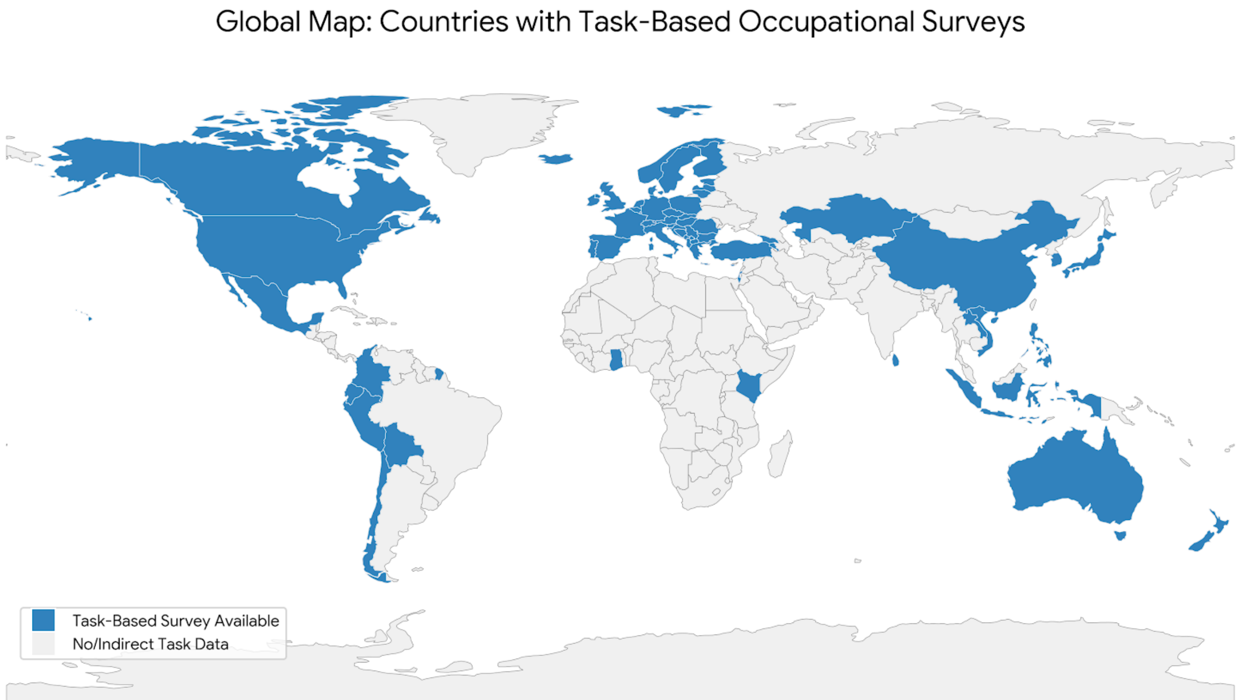


Figure 4: Global coverage of task-based surveys. Countries highlighted in blue have participated in dedicated task-focused surveys (O*NET, PIAAC, STEP, or ESJS) capturing granular skill usage. Note that for middle-income contexts like Ghana, Kenya, and Vietnam, data is sourced from the World Bank STEP program, whereas India currently relies on crosswalks or occupation-manual indices.

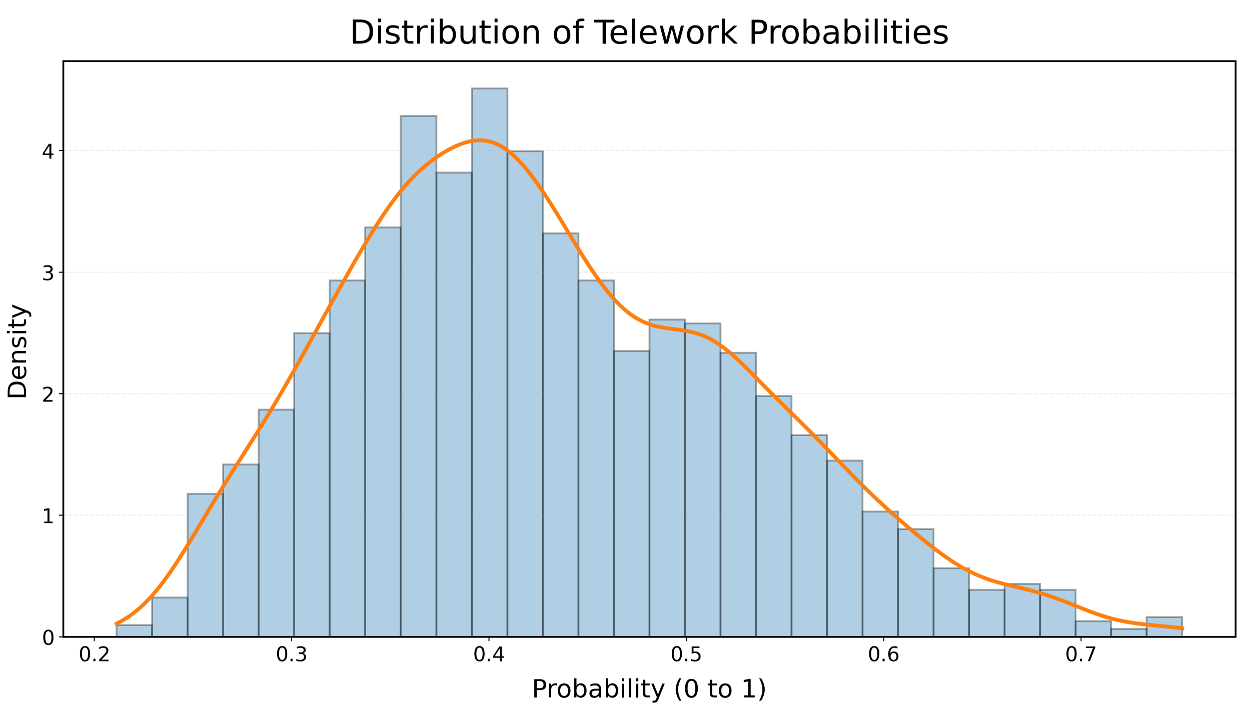


Figure 5: *Distribution of Predicted Probabilities generated using equation (17). The range lies between 0 and 0.79.*

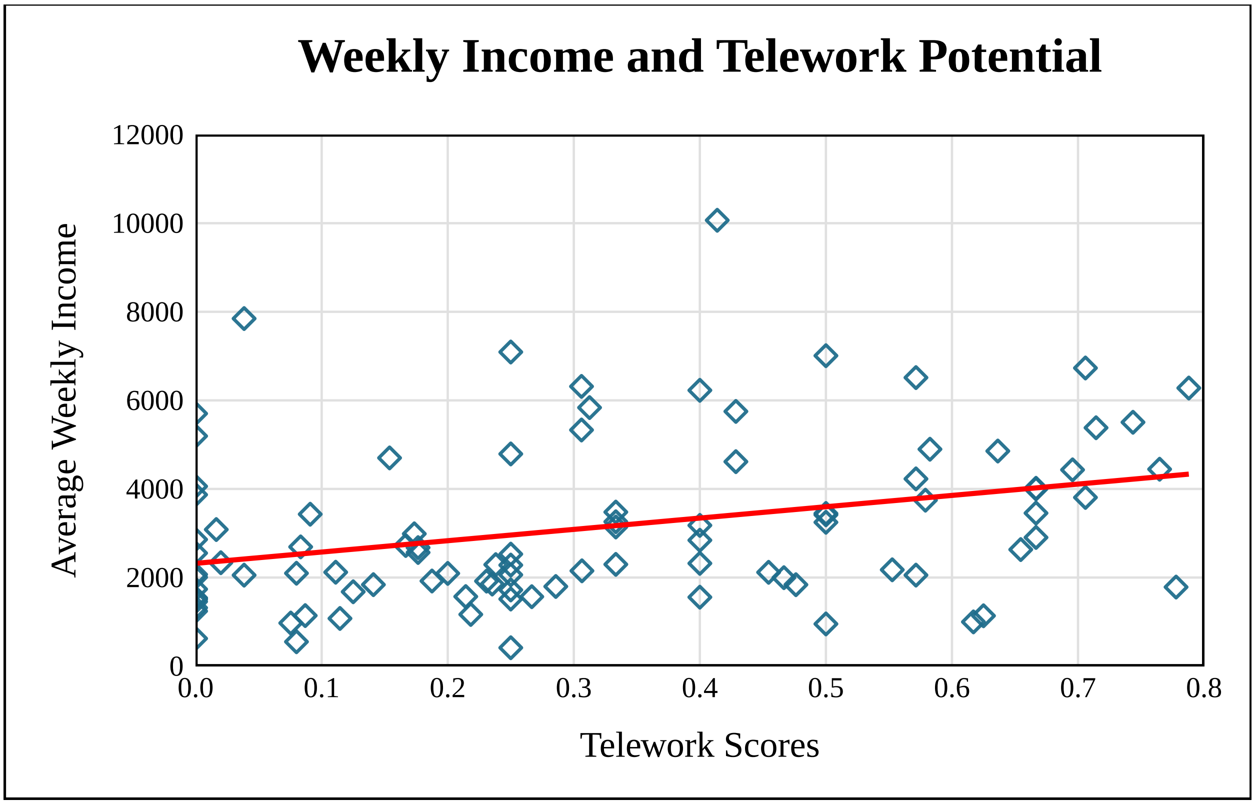


Figure 6: Occupations with higher telework potential fetch higher income.

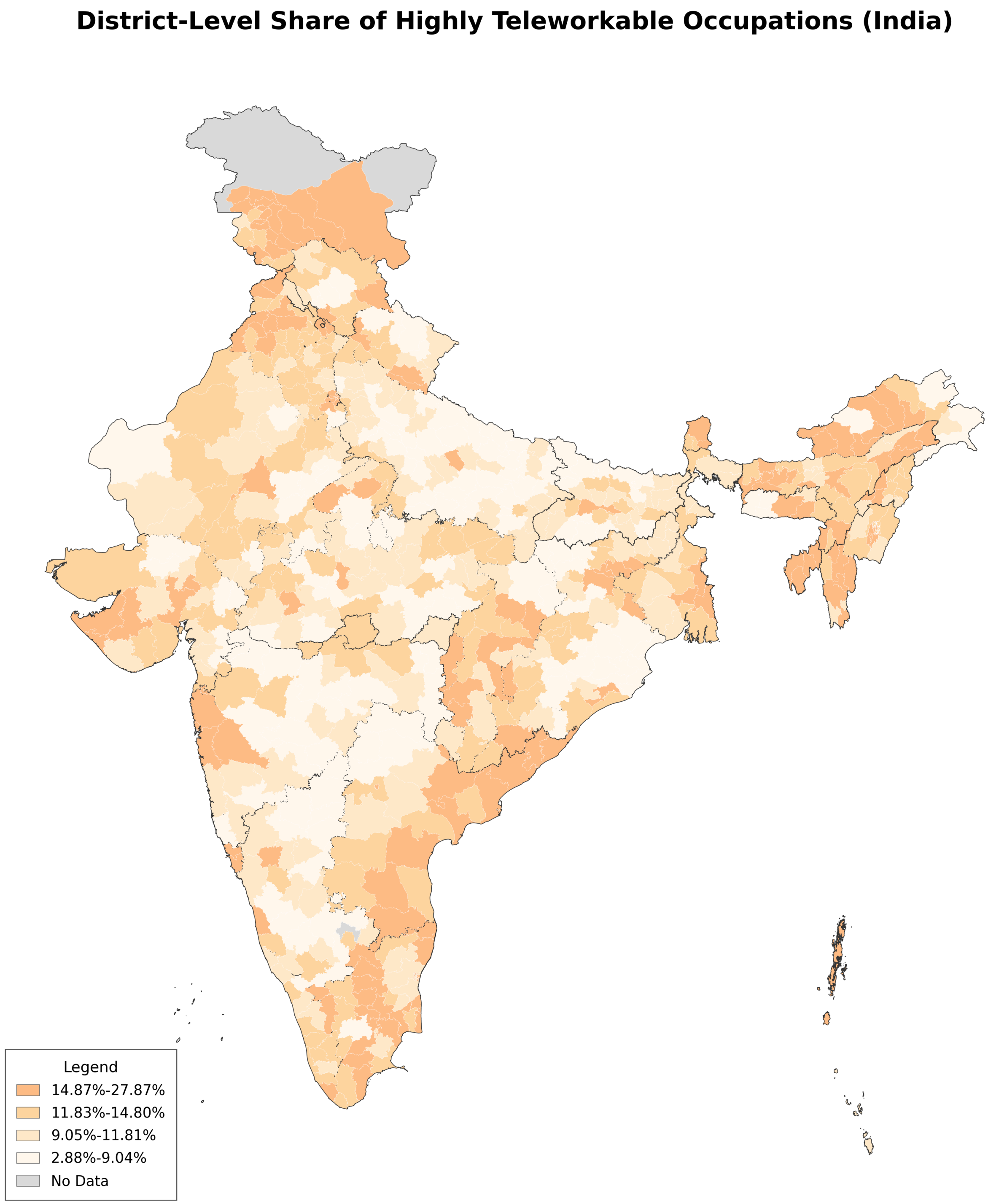
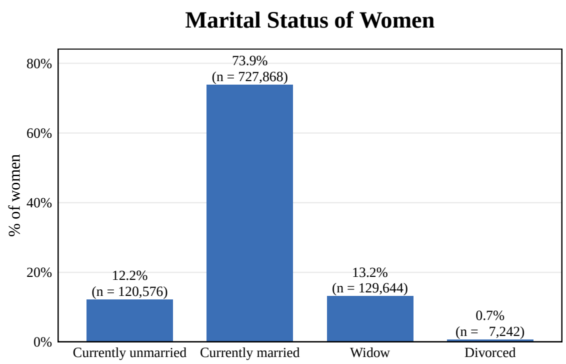
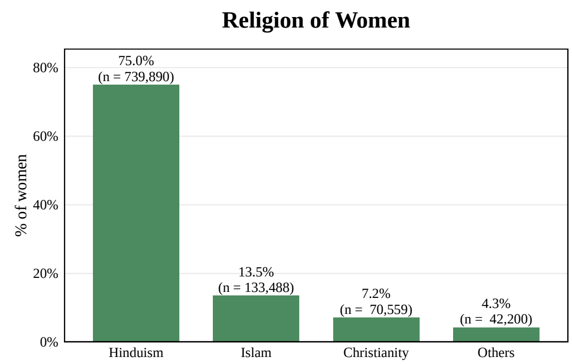


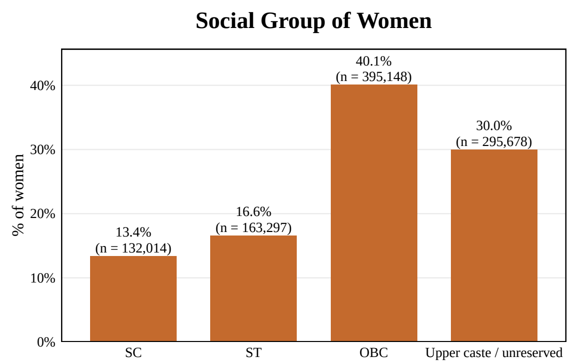
Figure 7: District-wise shares of 3-digit PLFS occupations with more than 50^{th} percentile of 8-digit teleworkable occupations



(a) Marital Status

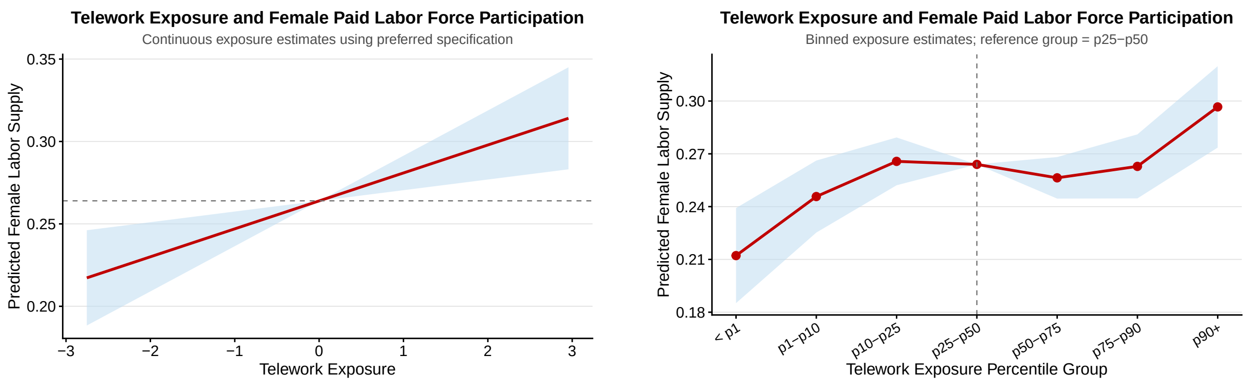


(b) Religion



(c) Social Group (Official umbrella of castes)

Figure 8: Distribution of Adult Female Population by their marital status, religion and social group using PLFS dataset.



(a) Continuous exposure

(b) Binned exposure

Figure 9: Predicted Effects of Telework Exposure on Female Paid Labor Supply.
Notes: Panel (a) plots predicted paid employment probability across the continuous distribution of telework exposure. Panel (b) replaces the continuous exposure variable with percentile bins and plots predicted participation with p25–p50 as reference bin. The monotonically increasing gradient across bins supports the linear relationship in equation (25). Shaded bands denote 95% confidence intervals. Standard errors are clustered at the district level.

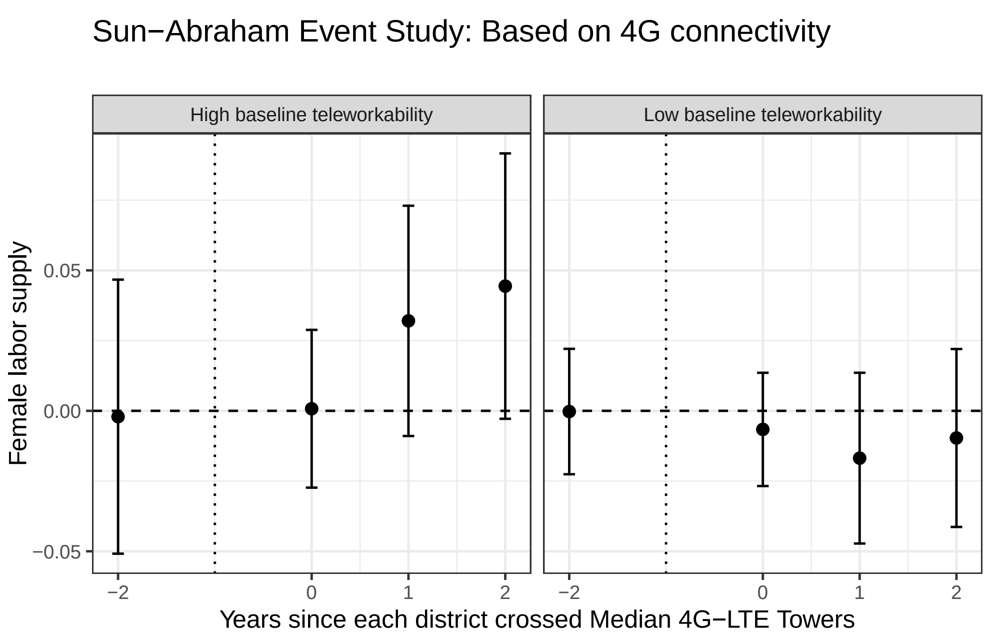


Figure 10: Event Study Estimates: Teleworkable Occupation Shares and 4G Internet Expansion.
Notes: The event year is defined as the first year in which a district crosses the 50th percentile of 4G-LTE tower density. High- and low-teleworkability districts are defined relative to the median 2017–2019 district share of teleworkable occupations. The omitted reference period is one year before crossing. Points show estimated coefficients and vertical bars show 95 percent confidence intervals.

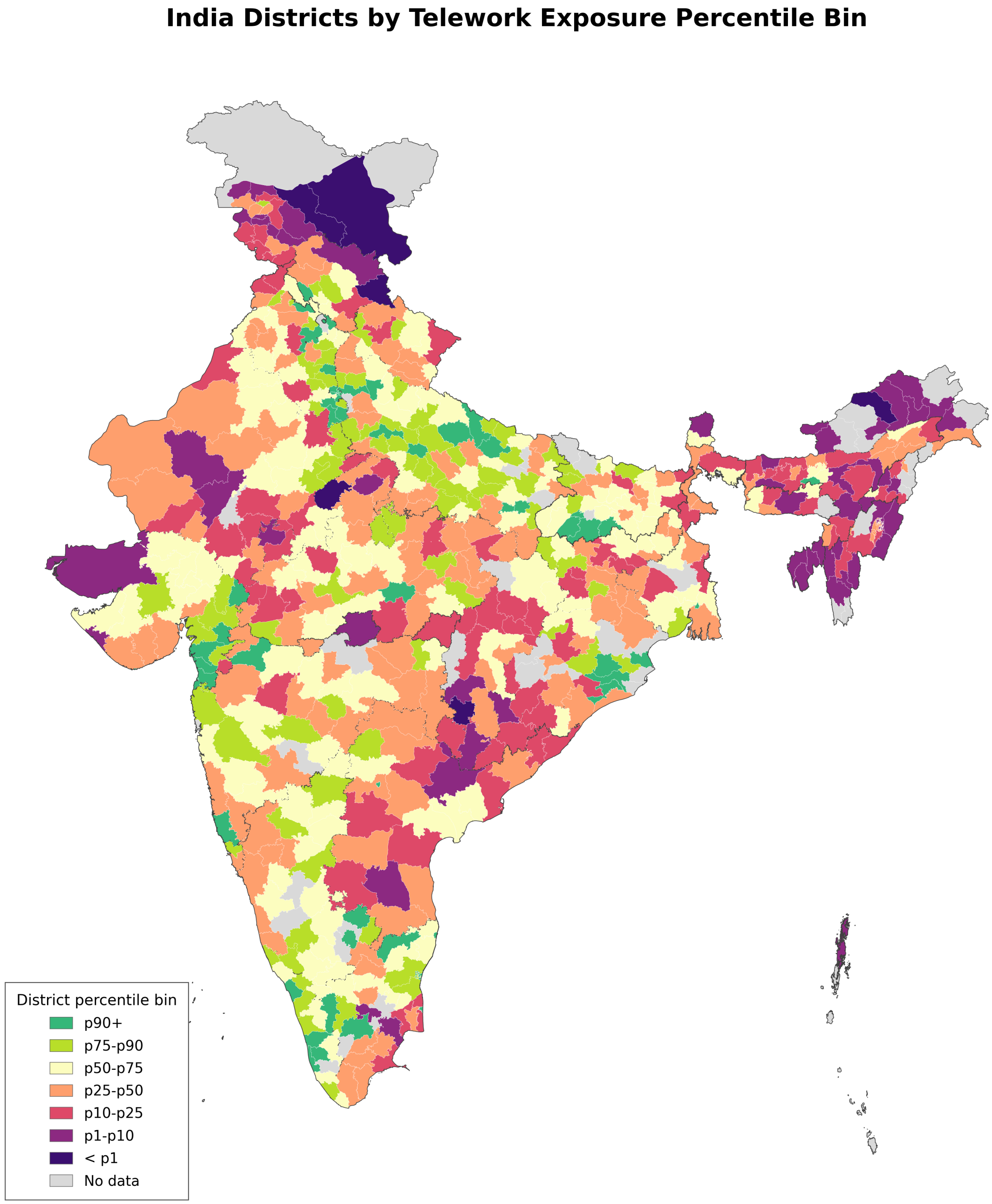


Figure 11: Distribution of Districts by telework exposure bins

Tables

Table 1: Summary statistics for continuous variables (PLFS)

Variable	**Mean**	**Std. Dev.**
Paid labor force participation	0.287	0.453
Age	41.181	15.598
Dependency Ratio	0.310	0.285
Weekly hours worked	10.001	18.374
Monthly per capita consumption expenditure	2,679.629	2,720.993
Regular wage earnings	1,150.160	6,320.896
Self-employment earnings	740.863	4,173.359
Casual wage earnings	36.297	244.058

Notes: The sample is restricted to women aged above 18. Monetary variables are reported in nominal rupees.

Table 2: Summary statistics for regression variables (NFHS)

Variable	**Mean**	**Std. Dev.**
Paid (Non-agricultural) labor	0.177	0.382
Household internet access	0.341	0.474
Household computer access	0.090	0.286
Allowed to go to market alone	0.572	0.495
Allowed to go to health facility alone	0.511	0.500
Allowed to go outside village/town alone	0.501	0.500
Allowed to go alone in all three domains	0.423	0.494
Age	30.118	9.828
No education	0.256	0.436
Primary education	0.122	0.327
Secondary education	0.495	0.500
Higher education	0.128	0.334
Never in union	0.248	0.432
Currently married	0.711	0.453
Widowed	0.030	0.170
Divorced	0.004	0.064
Separated / no longer living together	0.007	0.085

Notes: This table reports summary statistics for the dependent variables, mechanism outcomes, and individual-level demographic controls used in the NFHS regressions. For categorical demographic variables, entries are reported as indicator means and standard deviations for each category. Exposure variables and tower-density measures are omitted because they are constructed from external sources.

Table 3: Top 10 and bottom 10 teleworkable occupations

NCO (8-digit)	**Occupation Title**	**Pr(TW)**	**Manual Indexing (0/1)**
Panel A: Top 10 most teleworkable			
2431.0501	Market Research Associate-Sales	0.7513	1
2643.0401	Language Translator-Software	0.7504	1
2641.0901	Technical Writer-Product	0.7497	1
2511.0102	Engineer-Software Transition	0.7466	1
2641.0903	Technical Writer-Technical	0.7462	1
2511.0103	Engineer-Packaging	0.7459	1
2641.0902	Technical Writer – Application Development	0.7456	1
2512.0203	Design Engineer (Product Engineer)	0.7416	1
2431.0503	Market Research Associate-Product	0.7392	1
2643.0402	Language Translator-IT Services	0.7390	1
Panel B: Bottom 10 least teleworkable			
7223.0100	Tool Setter - General	0.2113	0
7223.2500	Ball Filling Machine Operator	0.2156	0
7223.1900	Rifling Machine Operator	0.2225	0
7223.2900	Profiling Machine Operator	0.2228	0
7223.2600	Ball Lapping Machine Operator	0.2275	0
8156.9900	Cutting, Lasting and Sewing	0.2280	0
8172.0400	Circular Saw Operator	0.2308	0
8156.0100	Pounding Machine Operator (FootWear)	0.2327	0
8156.1500	Sole Stitcher, Machine	0.2338	0
7223.2300	Power Press Operator, Metal	0.2346	0

Notes: This table reports top ten most and least teleworkable jobs from trained set. The Pr(TW) in the third column is the predicted probability that a job is teleworkable using the NLP approach (eq. **??**). The last column codes 0/1 based on whether Pr(TW) exceeds the threshold of 0.47521.

Table 4: Validation: Telework Exposure and Flexible Workplace Location

	Broad Flexible Location	**Broad Urban Flexible Location**	**Strict Urban Flexible Location**
Telework exposure	0.00515*	0.00397***	0.00294***
	(0.00263)	(0.00117)	(0.00103)
Individual controls	Yes	Yes	Yes
Lagged nightlights	Yes	Yes	Yes
District FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes
Observations	1,394,491	1,394,491	1,394,491
District clusters	624	624	624

Notes: This table reports validation estimates using reported workplace location as the outcome. Broad flexible location equals one for rural own-dwelling or adjacent workplace codes 10–13, urban own-dwelling or adjacent workplace codes 20–23, or no fixed workplace code 99. Broad urban flexible location equals one for urban codes 20–23 or code 99. Strict urban flexible location equals one for urban own-dwelling work code 20 or no fixed workplace code 99. All regressions include age, education, marital status, religion, social group, lagged nightlights, district fixed effects, year fixed effects, and state-by-year fixed effects. Standard errors clustered at the district level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 5: Telework Exposure and Female Paid Labor Force Participation

	Female Paid Labor			
	(1)	**(2)**	**(3)**	**(4)**
Telework exposure	0.0201***	0.0196***	0.0160***	0.0170***
	(0.0058)	(0.0054)	(0.0055)	(0.0053)
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Lagged nightlights	No	Yes	Yes	Yes
State-year fixed effects	No	No	Yes	Yes
Demographic controls	No	No	No	Yes
Mean female participation rate	0.287	0.287	0.287	0.287
Observations	703,249	703,249	703,249	703,170
R^2	0.0801	0.0801	0.0842	0.1176

Notes: All regressions are estimated using district and year fixed effects. The sample is restricted to women above age 18. Column (1) reports the baseline specification with district and year fixed effects. Column (2) adds lagged nightlights as time-varying district-level development trends. Column (3) further includes state-year fixed effects to account for differential state-level policies towards women empowerment. Column (4) incorporates demographic controls. Standard errors, clustered at the district level, are reported in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6: Falsification Tests: Telework Exposure and Placebo Outcomes

	Male Paid Labor	**Underage Labor**	**Log Bank Branch Density**	**Log Economic Growth**
Telework exposure	0.003	−0.002	0.053	−0.006
	(0.002)	(0.0017)	(0.042)	(0.004)
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Lagged nightlights	No	Yes	Yes	No
State-year fixed effects	No	No	Yes	Yes
Demographic controls	No	No	No	No
Observations	514,865	516,173	1,608,564	1,743,032
R^2	0.299	0.133	0.990	0.577

Notes: Column (1) reports the effect of telework exposure on male paid labor force participation. Column (2) reports the effect on paid labor force participation among individuals aged 5–18 years. Column (3) reports the effect on contemporaneous log bank branch density. Column (4) reports the effect on contemporaneous log economic growth. Economic growth data are available through 2022–2023. All regressions include district and year fixed effects. Additional controls and fixed effects are reported in the table. Standard errors, clustered at the district level, are reported in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 7: Robustness to Alternative Telework Exposure Thresholds

	Female Paid Labor					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Telework exposure	0.0159***	0.0157***	0.0140**	0.0170***	0.0184***	0.0183***
	(0.005)	(0.006)	(0.006)	(0.005)	(0.006)	(0.005)
Exposure threshold	All	p10	p25	p30	p75	p90
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Number of district fixed effects	624	624	624	624	624	624
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Lagged nightlights	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	703,170	703,170	703,170	703,170	703,170	703,170
R^2	0.1176	0.1176	0.1176	0.1176	0.1176	0.1177

Notes: This table reports robustness checks using alternative thresholds to classify occupations as teleworkable. Column (1) uses the unrestricted district-level telework share, without imposing an occupational teleworkability threshold. Columns (2)–(6) define teleworkable occupations using the indicated thresholds. Each exposure measure is constructed as the district-level share of teleworkable occupations interacted with lagged log cell-tower density, and then standardized. The sample is restricted to women above age 18. All regressions include district fixed effects, year fixed effects, state-year fixed effects, lagged nightlights, and demographic controls for age, education level, marital status, religion, and social group. Standard errors, clustered at the district level, are reported in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 8: Robustness to Minimum FSU Coverage

	Female Paid Labor			
	(1)	**(2)**	**(3)**	**(4)**
Telework exposure	0.0167***	0.0177***	0.0183***	0.0203***
	(0.00541)	(0.00543)	(0.00546)	(0.00588)
FSU percentile cutoff	1%	5%	10%	25%
Number of district fixed effects	615	596	564	448
Year fixed effects	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes
Lagged nightlights	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes
Observations	700,291	687,937	666,973	583,227
R^2	0.118	0.117	0.117	0.114

Notes: This table reports robustness checks that restrict the estimation sample to district-round cells with at least the indicated number of unique first-stage units (FSUs). The cutoffs correspond approximately to the 1st, 5th, 10th, and 25th percentiles of the district-round FSU distribution. All regressions are estimated using district, year, and state-year fixed effects. The sample is restricted to women above age 18. All specifications include lagged nightlights and demographic controls for age, education level, marital status, religion, and social group. Standard errors, clustered at the district level, are reported in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 9: Telework Exposure and Female Paid Labor Force Participation

	Female Paid Labor			
	(1)	**(2)**	**(3)**	**(4)**
Telework exposure	0.0204***	0.0198***	0.0168***	0.0176***
	(0.0059)	(0.0055)	(0.0056)	(0.0054)
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Lagged nightlights	No	Yes	Yes	Yes
State-year fixed effects	No	No	Yes	Yes
Demographic controls	No	No	No	Yes
Mean female participation rate	0.277	0.277	0.277	0.277
Observations	692,931	692,931	692,931	692,852
R^2	0.0797	0.0797	0.0836	0.1171

Notes: All regressions are estimated on the sample of women above age 18, restricting to district-year cells with at least 50 observations. Standard errors clustered at the district level are reported in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 10: Telework Exposure and Female Weekly Labor Hours

	Log Female Weekly Labor Hours			
	(1)	**(2)**	**(3)**	**(4)**
Telework exposure	0.0625***	0.0611***	0.0529***	0.0562***
	(0.0202)	(0.0188)	(0.0192)	(0.0186)
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Lagged nightlights	No	Yes	Yes	Yes
State-year fixed effects	No	No	Yes	Yes
Demographic controls	No	No	No	Yes
Observations	703,910	703,910	703,910	703,170
R^2	0.0748	0.0748	0.0787	0.1054

Notes: The dependent variable is the log of one plus total weekly labor hours, $\log(1 + \text{weekly hours})$. All regressions are estimated using district and year fixed effects. The sample is restricted to women above age 18. Standard errors, clustered at the district level, are reported in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 11: Telework Exposure and Female Paid Labor Force Participation: 4G Mobile Tower Exposure

	Female Paid Labor			
	(1)	**(2)**	**(3)**	**(4)**
Telework exposure	0.0076***	0.0075***	0.0064***	0.0064***
	(0.0015)	(0.0016)	(0.0017)	(0.0017)
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Lagged nightlights	No	Yes	Yes	Yes
State-year fixed effects	No	No	Yes	Yes
Demographic controls	No	No	No	Yes
Mean female participation rate	0.278	0.278	0.278	0.278
Observations	954,145	954,145	954,145	954,066
R^2	0.0835	0.0835	0.0882	0.1203

Notes: This table reports robustness checks using 4G cell-tower exposure instead of overall cell-tower exposure. The dependent variable is an indicator for female paid labor force participation. Telework exposure is constructed using the standardized interaction between district-level baseline teleworkability and 4G cell-tower density. The sample is restricted to women above age 18. Column (1) includes district and year fixed effects. Column (2) adds lagged nightlights as a time-varying district-level proxy for local economic development. Column (3) further includes state-year fixed effects to account for differential state-level trends and policies. Column (4) adds demographic controls for age, marital status, religion, social group, and education level. Standard errors, clustered at the district level, are reported in parentheses.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 12: Telework Exposure and Female Paid Labor Force Participation by Marital Status

	Married Women		**Unmarried Women**	
	(1a) **No Controls**	**(1b)** **Controls**	**(2a)** **No Controls**	**(2b)** **Controls**
Telework exposure	0.0183***	0.0195***	−0.0027	−0.0007
	(0.00655)	(0.00601)	(0.00848)	(0.00782)
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes
Lagged nightlights	No	Yes	No	Yes
Demographic controls	No	Yes	No	Yes
Observations	519,075	519,010	83,729	83,724
R^2	0.1110	0.1329	0.0990	0.2227

Notes: This table reports heterogeneous effects of marital status on the relationship between telework exposure and female labor supply. Columns (1a)–(1b) restrict the sample to married women. Columns (2a)–(2b) restrict the sample to unmarried women. Standard errors, clustered at the district level, are shown in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 22: Telework Exposure and Female Paid Labor Force Participation by Age Group

	Age 19–24 **(1)**	**Age 25–49** **(2)**	**Age 50–75** **(3)**
Telework exposure	0.0035	0.0177***	0.0203***
	(0.00762)	(0.00638)	(0.00692)
District fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes
Lagged nightlights	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes
Observations	109,691	385,974	192,312
R^2	0.1559	0.1703	0.1576

Notes: This table reports heterogeneity in the relationship between telework exposure and female paid labor force participation by age group. Standard errors, clustered at the district level, are reported in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 13: Telework Exposure and Female Paid Labor Force Participation by Husband's Teleworkability

	Not Teleworkable		**Teleworkable**	
	(1a)	**(1b)**	**(2a)**	**(2b)**
	No Controls	**Controls**	**No Controls**	**Controls**
Telework exposure	0.0283***	0.0269***	0.0043	0.0070
	(0.00674)	(0.00642)	(0.00845)	(0.00807)
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes
Lagged nightlights	Yes	Yes	Yes	Yes
Demographic controls	No	Yes	No	Yes
Observations	203,393	203,382	197,256	197,228
R^2	0.1155	0.1453	0.1611	0.1928

Notes: This table reports heterogeneity in the relationship between telework exposure and women's paid labor force participation by the teleworkability of the husband's occupation. Columns (1a) and (1b) restrict the sample to married women whose husbands are in non-teleworkable occupations. Columns (2a) and (2b) restrict the sample to married women whose husbands are in teleworkable occupations. All regressions include district fixed effects, year fixed effects, and state-year fixed effects. Columns (1a) and (2a) include lagged nightlights only; Columns (1b) and (2b) additionally include demographic controls for age, education level, marital status, religion, and social group. Standard errors, clustered at the district level, are reported in parentheses.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 14: Telework Exposure and Female Paid Labor Force Participation by Husband's Employment

	Regular Job		**Self-Employed**		**Casual Job**	
	Low TW	**High TW**	**Low TW**	**High TW**	**Low TW**	**High TW**
Telework exposure	0.0192*	−0.0026	0.0326***	0.0056	0.0164	0.0767*
	(0.00987)	(0.00907)	(0.00956)	(0.01005)	(0.01006)	(0.04006)
Observations	55,939	57,241	83,484	136,849	63,935	2,996
R^2	0.1314	0.1324	0.1497	0.2363	0.2087	0.3963
District fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Lagged nightlights	Yes	Yes	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports heterogeneous effects of telework exposure on women's paid labor force participation by the husband's employment type and the teleworkability of the husband's occupation. Low TW and High TW denote husbands in low- and high-teleworkable occupations, respectively. All regressions include lagged nightlights, district fixed effects, year fixed effects, state-year fixed effects, and demographic controls for age, education level, marital status, religion, and social group. Standard errors clustered at the district level are reported in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 15: Telework Exposure and Female Paid Labor Force Participation by Husband's Contract Length

	Regular Job		**Casual Job**	
	Short/No Contract	**Longer Contract**	**Short/No Contract**	**Longer Contra**
Panel B: With controls				
Telework exposure	0.0028	0.0223**	0.0180*	−0.1745
	(0.0078)	(0.0108)	(0.0099)	(0.2222)
Observations	74,180	39,455	64,028	311
R^2	0.1193	0.1605	0.2103	0.8796
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes
Lagged nightlights	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes

Notes: This table reports heterogeneous effects of telework exposure on women's paid labor force participation by the husba employment type and contract length. Short/no contract includes husbands with no written contract or a written contrac one year or less. Longer contract includes husbands with written contracts of more than one year. Panel A reports specificat without lagged nightlights and demographic controls. Panel B adds lagged nightlights and demographic controls. All specificat include district fixed effects, year fixed effects, and state-by-year fixed effects. Standard errors clustered at the district leve reported in parentheses.

The casual longer-contract cell contains only 311 observations and should be interpreted with caution.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 16: Telework Exposure and Female Paid Labor Force Participation by Monthly Per-Capita Consumption Expenditure

	At or Above Median MPCE		Below Median MPCE	
	(1a)	**(1b)**	**(2a)**	**(2b)**
	No Controls	**Controls**	**No Controls**	**Controls**
Telework exposure	0.0188***	0.0189***	0.0054	0.0062
	(0.00549)	(0.00517)	(0.00782)	(0.00759)
MPCE cutoff	$\geq$ 2,000	$\geq$ 2,000	$<$ 2,000	$<$ 2,000
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes
Lagged nightlights	No	Yes	No	Yes
Demographic controls	No	Yes	No	Yes
Observations	400,098	400,068	303,148	303,099
R^2	0.0637	0.1120	0.1164	0.1365

Notes: This table reports heterogeneity in the relationship between telework exposure and female paid labor force participation by monthly per-capita consumption expenditure (MPCE), with median value being Rs. 2,000. The sample is restricted to women above age 18. Standard errors, clustered at the district level, are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 17: Telework Exposure and Female Paid Labor Force Participation by Crime Against Women

	Below-Median Crime		**Above-Median Crime**	
	(1a) **No Controls**	**(1b)** **Controls**	**(2a)** **No Controls**	**(2b)** **Controls**
Telework exposure	−0.0001	−0.0004	0.0190**	0.0223**
	(0.0104)	(0.0104)	(0.0092)	(0.0090)
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes
Lagged nightlights	Yes	Yes	Yes	Yes
Demographic controls	No	Yes	No	Yes
Observations	258,823	258,782	307,678	307,646
R^2	0.1041	0.1305	0.0735	0.1077

Notes: This table reports heterogeneous effects of telework exposure on women's paid labor force participation by district-level crime against women. Median number of reported crimes against women is 560 in India. Standard errors clustered at the district level are reported in parentheses.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 18: Telework Exposure and Female Paid Labor Force Participation by Dependency Ratio

	High Dependency		**Low Dependency**	
	(1a) **No Controls**	**(1b)** **Controls**	**(2a)** **No Controls**	**(2b)** **Controls**
Telework exposure	0.0170***	0.0187***	0.0158**	0.0152**
	(0.00598)	(0.00563)	(0.00694)	(0.00667)
Dependency-burden cutoff	≥ 0.25	≥ 0.25	< 0.25	< 0.25
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes
Lagged nightlights	No	Yes	No	Yes
Demographic controls	No	Yes	No	Yes
Observations	367,363	367,319	335,886	335,851
R^2	0.0899	0.1233	0.0852	0.1197

Notes: This table reports heterogeneity in the relationship between telework exposure and female paid labor force participation by household dependency burden. High dependency is defined as a household with dependency ratio greater than or equal to 50^{th} percentile value (0.25), while low dependency burden is defined as a household with dependency ratio below this cutoff. Standard errors, clustered at the district level, are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 19: Telework Exposure and Female Paid Labor Force Participation among Married Women by Child Age Group

	$<$ 5 years	**5–10 years**	**11–15 years**	**16–18 years**
	(1)	(2)	(3)	(4)
Telework exposure	0.0170**	0.0157*	0.0055	0.0138
	(0.0075)	(0.0083)	(0.0079)	(0.0089)
Observations	158,044	171,147	153,236	117,838
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes
Lagged nightlights	Yes	Yes	Yes	Yes
Demographic controls	Yes	Yes	Yes	Yes

Notes: This table reports controlled estimates of the effect of telework exposure on paid labor force participation among married women in households with at least one child in various age groups. Standard errors clustered at the district level are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 20: Telework Exposure and Female Paid Labor Force Participation by Job Contract Status

	Has Job Contract		**No Job Contract**	
	(1a) **Baseline**	**(1b)** **Controls**	**(2a)** **Baseline**	**(2b)** **Controls**
Telework exposure	0.0089	0.0103*	−0.0022	−0.0012
	(0.00572)	(0.00572)	(0.00737)	(0.00727)
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes
Lagged nightlights	Yes	Yes	Yes	Yes
Demographic controls	No	Yes	No	Yes
Observations	22,151	22,151	48,591	48,590
R^2	0.1250	0.1375	0.1309	0.1387

Notes: This table reports heterogeneity in the relationship between telework exposure and female paid labor force participation by job contract status. Columns (1a)–(1b) restrict the sample to women with a job contract. Columns (2a)–(2b) restrict the sample to women without a job contract. Standard errors, clustered at the district level, are reported in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 21: Telework Exposure and Female Paid Labor Force Participation by Technical Degree Status among College-Educated Women

	Non-Technical Degree		**Technical Degree**	
	(1a) Baseline	**(1b) Controls**	**(2a) Baseline**	**(2b) Controls**
Telework exposure	−0.0025	−0.0017	0.0409	0.0475*
	(0.00974)	(0.00949)	(0.02603)	(0.02449)
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
State-year fixed effects	Yes	Yes	Yes	Yes
Lagged nightlights	Yes	Yes	Yes	Yes
Demographic controls	No	Yes	No	Yes
Observations	77,323	77,323	9,099	9,099
R^2	0.0684	0.1056	0.1370	0.1943

Notes: This table reports heterogeneity in the relationship between telework exposure and female paid labor force participation by technical degree status among college-educated women. Columns (1a)–(1b) restrict the sample to women with non technical higher education. Columns (2a) and (2b) restrict the sample to women with technical college education. Standard errors, clustered at the district level, are reported in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 23: Mechanism: Telework Exposure and Women's Monthly Income

	Log Monthly Income			
	(1)	**(2)**	**(3)**	**(4)**
Telework exposure	0.1075***	0.1134***	0.1067***	0.1090***
	(0.0356)	(0.0342)	(0.0326)	(0.0326)
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Lagged nightlights	No	Yes	Yes	Yes
State-year fixed effects	No	No	Yes	Yes
Demographic controls	No	No	No	Yes
Mean log monthly income	2.349	2.349	2.349	2.349
Observations	703,901	703,901	703,901	703,161
R^2	0.0684	0.0684	0.0720	0.1006

Notes: The dependent variable is log(1 + monthly income), where monthly income includes wage earnings, regular wage earnings, and self-employment earnings. The log transformation is used to retain women with zero income, since many women are out of the labor force. The sample is restricted to women above age 18, and observations with negative monthly income are excluded. Column (1) reports the baseline specification with district and year fixed effects. Column (2) adds lagged nightlights to account for time-varying district-level development trends. Column (3) further includes state-year fixed effects to account for differential state-level policies and shocks. Column (4) incorporates demographic controls for age, education, religion, social group, and marital status. Standard errors, clustered at the district level, are reported in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 24: Mechanism: Telework Exposure and Unpaid Household Labor

	Unpaid Household Labor as Primary Activity			
	(1)	**(2)**	**(3)**	**(4)**
Telework exposure	-0.0199^{**}	-0.0186^{**}	-0.0129^{*}	-0.0139^{*}
	(0.0079)	(0.0076)	(0.0075)	(0.0072)
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Lagged nightlights	No	Yes	Yes	Yes
State-year fixed effects	No	No	Yes	Yes
Demographic controls	No	No	No	Yes
Mean dependent variable	0.635	0.635	0.635	0.635
Observations	519,720	519,720	519,720	519,693
R^2	0.1128	0.1128	0.1191	0.1673

Notes: The dependent variable is an indicator equal to one if unpaid household labor is reported as the woman's primary activity. The sample is restricted to women above age 18. Column (1) includes district and year fixed effects. Column (2) adds lagged nightlights to account for time-varying district-level development trends. Column (3) further includes state-year fixed effects. Column (4) adds demographic controls for age, education, religion, social group, and marital status. Standard errors, clustered at the district level, are reported in parentheses.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 25: Mechanism: Telework Exposure and Participation in Physical-Presence Sectors

	Physical-Presence Sector Participation			
	(1)	**(2)**	**(3)**	**(4)**
Telework exposure	0.0113	0.0116	0.0114	0.0061
	(0.0097)	(0.0089)	(0.0088)	(0.0070)
District fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes
Lagged nightlights	No	Yes	Yes	Yes
State-year fixed effects	No	No	Yes	Yes
Demographic controls	No	No	No	Yes
Observations	170,757	170,757	170,757	170,747
R^2	0.1843	0.1843	0.1904	0.3514

Notes: The dependent variable is an indicator equal to one if the woman participates in a sector that requires physical presence. Physical-presence sectors include agriculture, mining and quarrying, manufacturing, electricity and water supply, and construction, based on two-digit NIC-2008 industry divisions. The sample is restricted to women above age 18. Column (1) includes district and year fixed effects. Column (2) adds lagged nightlights to account for time-varying district-level development trends. Column (3) further includes state-year fixed effects. Column (4) adds demographic controls for age, education, marital status, religion, and social group. Standard errors, clustered at the district level, are reported in parentheses.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 26: Shift Share IV Estimates for Female Labor Supply

	Dependent Variable: Participation in non-agricultural labor	
	(1)	(2)
Panel A: Second Stage		
Telework exposure	0.0388***	0.0368***
	(0.0130)	(0.0126)
Panel B: First Stage		
Shift-Share instrument	0.4807***	0.4806***
	(0.0327)	(0.0327)
Panel C		
Reduced form	0.0187***	0.0177***
	(0.0063)	(0.0061)
First-stage partial F	216.44	216.49
First-stage partial R^2	0.3378	0.3378
Shea's partial R^2	0.3378	0.3378
Durbin test p-value	0.000006	0.000008
Wu-Hausman test p-value	0.000006	0.000008
Wooldridge score test p-value	0.000019	0.000023
Mean of dependent variable	0.1774	0.1775
Observations	140,271	140,076
District clusters	627	627
District fixed effects	Yes	Yes
Survey-round fixed effects	Yes	Yes
Individual controls	No	Yes

Notes: The dependent variable equals 1 if the respondent is in non-agricultural labor and 0 if she is out of the workforce; agricultural labor is excluded from the estimation sample. The endogenous regressor is the standardized district telework share interacted with the log of lagged extended tower density, where the lagged tower year is 2012 for NFHS-4 and 2016 for NFHS-5. The excluded instrument is the standardized district telework share interacted with national 4G growth. Controlled specifications include age, caste/tribe, education, and marital status. Standard errors clustered at the district level are reported in parentheses. The model is exactly identified, so no overidentification statistic is available.
Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 27: Mechanism: Reduced-Form Effects on Household Internet Access

	(1) Uncontrolled	(2) Controlled
Shift-Share instrument	0.0225***	0.0214***
	(0.0077)	(0.0075)
Mean of dependent variable	0.3389	0.3392
Observations	1,381,713	1,379,620
District clusters	676	676
District fixed effects	Yes	Yes
Survey-round fixed effects	Yes	Yes
Individual controls	No	Yes

Notes: Entries report reduced-form coefficients from regressions of household internet access on the standardized Shift-Share instrument. Controlled specifications include age, caste/tribe, education, and marital status. Standard errors clustered at the district level are reported in parentheses.
Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 28: Mechanism: Reduced-Form Effects on Household Computer Access

	(1) Uncontrolled	(2) Controlled
Shift-Share instrument	0.0105***	0.0089***
	(0.0026)	(0.0024)
Mean of dependent variable	0.0898	0.0898
Observations	1,381,713	1,379,620
District clusters	676	676
District fixed effects	Yes	Yes
Survey-round fixed effects	Yes	Yes
Individual controls	No	Yes

Notes: Entries report reduced-form coefficients from regressions of household computer access on the standardized Shift-Share instrument. Controlled specifications include age, caste/tribe, education, and marital status. Standard errors clustered at the district level are reported in parentheses.
Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 29: Mechanism: Reduced-Form Effects on Flexibility to Move Alone

	(1)	(2)
Shift-Share instrument	0.1361*	0.1256*
	(0.0699)	(0.0675)
Mean of dependent variable	0.4191	0.4191
Observations	104,240	104,240
District clusters	676	676
District fixed effects	Yes	Yes
Survey-round fixed effects	Yes	Yes
Individual controls	No	Yes

Notes: The movement index is the mean of three indicators for whether the woman is allowed to go alone to the market, a health facility, and outside the village. The all-three measure equals 1 if all three underlying mobility indicators equal 1. Controlled specifications include age, caste/tribe, education, and marital status. Standard errors clustered at the district level are reported in parentheses.
Significance levels: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Table 30: Baseline Cost-Benefit Analysis of 4G Expansion

	Value
A. Parameters	
A1. Estimated effect on female labor force participation	0.0170
A2. Standard error of estimated effect	0.0053
A3. Number of districts in main analysis sample	95
B. Translating the Estimate into Annual Benefits	
B1. Female population in sample districts[a]	128,453,579
B2. Additional women employed annually (= B1 $\times$ 0.017)	2,183,711
B3. Aggregate annual earnings benefit (Rs.)	218,967,964,168
C. Baseline Annual Cost-Benefit Analysis	
C1. Aggregate annualized cost, baseline benchmark (Rs.)	34,374,190,912
C2. Aggregate annual net benefit (= B3 $-$ C1) (Rs.)	184,593,773,256
C3. Aggregate benefit-cost ratio (= B3 / C1)	6.370
D. District-Level Distribution, Baseline Benchmark	
D1. Mean district-level benefit-cost ratio	40.538
D2. Median district-level benefit-cost ratio	10.386
D3. 25th percentile district-level benefit-cost ratio	4.205
D4. 75th percentile district-level benefit-cost ratio	23.806
D5. Share of districts with positive net benefits	0.937

Notes: The table reports the preferred baseline welfare calculation. Annual benefits are computed as the estimated increase in female labor force participation multiplied by district female population and district annual female earnings. Annual costs use the baseline official site-cost benchmark from the national 4G saturation project, already annualized in the input file.

[a] Female population is proxied by district female population from Census 2011. This is a favorable assumption because the denominator is not restricted to working-age women.

Table 31: CBA: Robustness and Sensitivity Analysis

	Low Cost	**Mid Cost**	**High Cost**
Panel A. Cost Benchmark Sensitivity			
Aggregate annual benefit (Rs.)	218,967,964,168	218,967,964,168	218,967,964,168
Aggregate annual cost (Rs.)	20,297,648,282	23,511,140,161	34,374,190,912
Aggregate annual net benefit (Rs.)	198,670,315,886	195,456,824,007	184,593,773,256
Aggregate benefit-cost ratio	10.788	9.313	6.370
Share of districts with positive net benefits	0.989	0.968	0.937
Panel B. Effect, Wage, and Fiscal Sensitivity			
		Value	
Aggregate annual net benefit, lower 95% effect and baseline cost (Rs.)		50,791,466,681	
Aggregate annual net benefit, main effect and baseline cost (Rs.)		184,593,773,256	
Aggregate annual net benefit, upper 95% effect and baseline cost (Rs.)		318,396,079,831	
Aggregate annual net benefit, conservative wage measure and baseline cost (Rs.)		13,623,704,037	
Aggregate annual net benefit, main effect and baseline cost with 15% deadweight loss (Rs.)		179,437,644,619	
Lower 95% effect, baseline cost: aggregate BCR		2.478	
Main effect, baseline cost: aggregate BCR		6.370	
Upper 95% effect, baseline cost: aggregate BCR		10.263	
Conservative wage measure, baseline cost: aggregate BCR		1.396	
Baseline cost with 15% deadweight loss: aggregate BCR		5.539	
Share of districts with positive net benefits, baseline cost with deadweight loss		0.937	

Notes: Panel A holds aggregate annual benefits fixed and varies only the official per-site cost benchmark. Low cost uses the Rs. 0.788 crore per-site benchmark from the 7,287-village aspirational districts project. Mid cost uses the Rs. 0.913 crore per-site benchmark from the 502-village project. High cost uses the Rs. 1.334 crore per-site benchmark from the national 4G saturation project. Panel B varies the employment effect, the wage measure, and the fiscal treatment of public cost. The deadweight-loss exercise applies a 15% markup to annualized public cost as a fiscal sensitivity check.

Appendix

A Derivations for the Theoretical Framework

This appendix provides derivations for the value comparisons discussed in Section 2. 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

$$V_T > V_O. \tag{39}$$

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

$$V_T = u(y_h + w_T L, \ell_T, f(d_T)) - \tau_T v(L) - \phi z(d_T), \tag{40}$$

where

$$\ell = 1 - L - d_T. \tag{41}$$

The value of office work is

$$V_O = u(y_h + w_O L, \ell_O, f(d_O)) - \tau_O v(L), \tag{42}$$

where

$$\ell = 1 - (1 + t_O)L - d_O. \tag{43}$$

Using a first-order approximation around a common allocation gives

$$V_T - V_O \approx u_c(w_T - w_O)L + u_H\{f(d_T) - f(d_O)\} + (\tau_O - \tau_T)v(L) - \phi z(d_T). \tag{44}$$

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

$$u_c(w_T - w_O)L + u_\ell t_O L + (\tau_O - \tau_T)v(L) - \phi z(d_T) > 0. \tag{45}$$

Rearranging yields

$$w_O - w_T < \frac{u_\ell}{u_c} t_O + \frac{(\tau_O - \tau_T)v(L)}{u_c L} - \frac{\phi z(d_T)}{u_c L}. \tag{46}$$

A.2 Telework versus No Paid Work

Telework is preferred to no paid work if

$$V_T > V_N. \tag{47}$$

The value of no paid work is

$$V_N = u(y_h, \ell, f(d_N)). \tag{48}$$

Using a first-order approximation,

$$V_T - V_N \approx u_c w_T L + u_H\{f(d_T) - f(d_N)\} - \tau_T v(L) - \phi z(d_T). \tag{49}$$

Therefore, telework is preferred to no paid work if

$$u_c w_T L > \tau_T v(L) + \phi z(d_T) + u_H\{f(d_N) - f(d_T)\}. \tag{50}$$

A.3 Office Work versus No Paid Work

Office work is preferred to no paid work if

$$V_O > V_N. \tag{51}$$

Using a first-order approximation,

$$V_O - V_N \approx u_c w_O L + u_H\{f(d_O) - f(d_N)\} - \tau_O v(L). \tag{52}$$

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

$$\ell_N - \ell_O = (1 + t_O)L. \tag{53}$$

Thus, office work is preferred to no paid work if

$$u_c w_O L > \tau_O v(L) + u_\ell(1 + t_O)L + u_H\{f(d_N) - f(d_O)\}. \tag{54}$$

Equivalently,

$$w_O > \frac{\tau_O v(L)}{u_c L} + \frac{u_\ell}{u_c}(1 + t_O) + \frac{u_H\{f(d_N) - f(d_O)\}}{u_c L}. \tag{55}$$

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

$$\frac{\partial t_T}{\partial F} < 0, \qquad \frac{\partial \tau_T}{\partial F} < 0. \tag{56}$$

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,

$$\frac{\partial (V_T - V_N)}{\partial F} > 0 \tag{57}$$

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

$$\frac{\partial (V_T - V_O)}{\partial F} > 0 \tag{58}$$

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 Construction of Telework Scores using Supervised Text Classifier

B.1 Evidence-tag dictionary of phrases

Table 32: 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 32: 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.

Table 33: Threshold selection for binary teleworkability classification.

	Threshold	**Bal. Acc.**	**F1**	**ROC–AUC**	**PR–AUC**
F1-optimal	**0.475**	0.910	**0.895**	0.981	0.976
Youden-J opt.	**0.475**	0.910	**0.895**	0.981	0.976
Default ($\tau = 0.50$)	0.500	0.895	0.882	0.981	0.976

Notes: This table compares alternative probability cutoffs used to classify occupations into binary groups based on their predicted teleworkability probabilities, $\widehat{TW}_o(\tau) = \mathbf{1}\{\widehat{\Pr}(TW_o) \geq \tau\}$. Bal. Acc. denotes balanced accuracy. ROC–AUC and PR–AUC are threshold-free ranking measures. See Appendix B.3 for details about NLP terms.

Table 34: Precision, Recall, F1 score, and Confusion Matrix (Teleworkability classifier).

	Precision	**Recall**	**F1**	**N**
1 - Teleworkable	0.94949	0.97917	**0.96410**	96
0 - Not teleworkable	0.98450	0.96212	**0.97318**	132
Accuracy			0.96930	228
Macro Average	0.96700	0.97064	**0.96864**	228
Weight Average	0.96976	0.96930	**0.96936**	228

Notes: This table presents binary classification based on F1 optimal threshold ($\tau = 0.47521$) using the training set. The overall classification accuracy F1 equals 0.97. See Appendix B.3 for details about NLP terms.

B.2 Confusion Matrix

True Value		ML generated indicator: **0 (Not teleworkable)**	ML generated indicator: **1 (Teleworkable)**
	0 (Not teleworkable)	True Negatives (55.7%)	False Positives (2.19%)
	1 (Teleworkable)	False Negatives (0.88%)	True Positives (41.23%)

Table 35: Confusion Matrix using the training set of $N = 228$ occupations. It compares how many of the model generated telework scores match with my manual assigned binary indicator (0/1).

B.3 NLP Terminology

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

$$\text{precision} = \frac{\text{True Positives}}{\text{True Positives+False Positives}} \tag{59}$$

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

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

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

$$\text{Specificity} = \frac{\text{True Negatives}}{\text{True Positives+False Negatives}} \tag{61}$$

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

$$\text{Sensitivity} = \frac{\text{True Positives}}{\text{True Positives+False Negatives}} \tag{62}$$

F1 Score is the weighted average of Precision and Recall.It is calculated as:

$$\text{F1} = 2 \times \frac{\text{Precision}\times\text{Recall}}{\text{Precision+Recall}} \tag{63}$$

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:

$$\mathbf{J} = \text{Sensitivity+Specificity-1} \tag{64}$$

Any value τ that maximizes eq. (64) is the optimal threshold choice.

B.4 External Validation

Benchmarking against Dingel & Neiman (2020). To assess how the ML-based telework measure compares with an established benchmark, I contrast my predictions with the teleworkability indicator proposed by Dingel and Neiman (2020) (Dingel and Neiman, 2020). Since the DN measure is defined for U.S. O*NET-SOC occupations, I concord it to Indian NCO occupations using a structured crosswalk procedure.

Title-based matching

This section explains how the Python script matches Indian NCO–2015 occupations to U.S. O*NET–SOC occupations using *title similarity* only (not task descriptions).

A. Title normalization (`norm_title`). For every NCO title and every O*NET title, the code creates a *normalized* version by:

- converting all text to lowercase;
- removing punctuation and separators (slashes, hyphens, and parentheses);
- replacing "&" with "and";
- removing common stop-words (e.g., *and, of, manager, supervisor, general, services*, etc.); and
- keeping the remaining tokens and joining them back into a single string.

As a result, the matching is driven by the remaining "content words" after filtering.

B. Similarity score (`blended_score`). For each normalized NCO title q, the code compares it to every normalized O*NET title and computes two string-similarity measures:

- `token_set_ratio(`q`, onet_title)`: emphasizes word overlap while ignoring word order; and
- `partial_ratio(`q`, onet_title)`: emphasizes cases where one title is largely contained in the other.

These are combined into a single 0–100 similarity score:

$$\texttt{match\_score} = 0.7 \cdot \texttt{token\_set\_ratio} + 0.3 \cdot \texttt{partial\_ratio}. \tag{65}$$

C. Best match (`TOPK=1`). The script keeps only the single best O*NET title (the one with the highest `match_score`) for each NCO title. It records:

- `best_onetsoccode`,
- `best_onet_title`, and
- the DN/O*NET telework label (`teleworkable`) from `occupations_workathome.csv` for that best match.

D. "Matched" indicator (`MATCH_CUTOFF = 80`). A binary flag is defined as:

$$\texttt{matched} = \mathbf{1}\{\texttt{match\_score} \geq 80\}. \tag{66}$$

Therefore, "how many NCO occupations match O*NET by title similarity" is the count of observations with `matched = 1`.

E. "Match probability" (`match_prob`). The code constructs a convenience rescaling:

$$\texttt{match\_prob} = \left(\frac{\texttt{match\_score}}{100}\right)^2. \tag{67}$$

This is *not* a statistical probability. It is a monotone transformation that compresses low scores and spreads high scores.

F. DN trigger vs. DN teleworkable. Two conceptually related but distinct variables appear in your output:

- `DN_trigger` is computed from `evidence_top / evidence_dn` inside the NCO text pipeline. It flags whether any DN-style "physical presence" evidence tag fires in the *NCO description*.
- `teleworkable` (DN teleworkable) is the *O*NET/DN label* attached to the best-matched O*NET occupation in `occupations_workathome.csv`.

These are related in spirit, but they are not the same construct and need not coincide for a given occupation.

B.5 Counts independent of τ (title matching only)

Using the script's exact rules (`TOPK=1` and `match_score` ≥ 80):

- **Matched by title similarity:** 773 NCO–2015 occupations (out of 3,448; $\approx 22.4\%$).
- **Within the matched sample (773), DN-teleworkable:** 313 occupations ($\approx 40.5\%$ of matched), where DN-teleworkable is defined by the matched O*NET occupation's DN label.

This answers: irrespective of the ML cutoff τ, how many NCO titles match O*NET titles by similarity, and within that matched sample, how many are teleworkable under the DN criterion.

DN Indicator	ML generated indicator: 0 (Not teleworkable)	ML generated indicator: 1 (Teleworkable)
0 (Not teleworkable)	324 (41.94%)	255 (32.99%)
1 (Teleworkable)	91 (11.77%)	103 (13.33%)

Figure 12: Confusion Matrix comparing Dingel & Neiman (2020) classification with ML-generated telework indicator (N=773).

B.5.1 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.

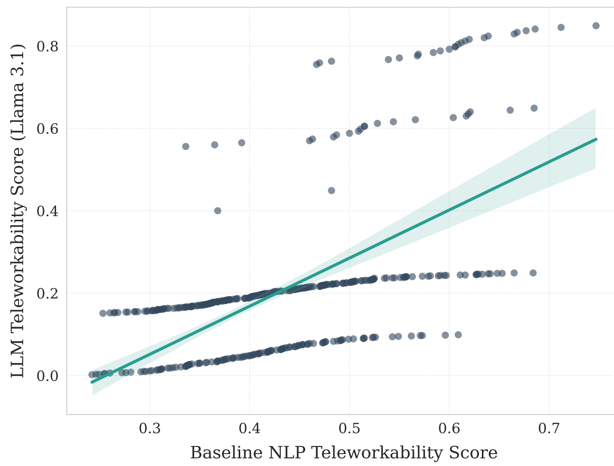


Figure 13: Comparison between NLP and LLM generated telework scores.

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.

Table 36: 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	0.747
2412.0200	Financial Analyst	0.988	0.712
2641.0801	Associate-Learning	0.975	0.686
1330.0101	Communication Analyst	0.962	0.677
2519.0501	Quality Engineer	0.950	0.668
3118.0200	Draughtsperson, Civil	0.938	0.665
3521.0511	Sound Editor	0.925	0.639
2512.0205	Junior Software Developer	0.912	0.635
2641.0602	Script Researcher	0.900	0.620
2641.0302	Script Editor	0.888	0.616
Panel B: Bottom 10 by LLM-generated telework score			
8152.0700	Sock Knitter/Knitting machine	0.002	0.242
7523.1100	Tenoning Machine Operator	0.003	0.246
8131.7000	Tablet Machine Operator	0.005	0.249
8157.0100	Washing Machine Operator	0.006	0.254
8160.87	Cutting Machine Operator, Tobacco	0.008	0.255
8171.0100	Chipper man, Paper Pulp	0.010	0.260
8112.0700	Stone Sawyer, Machine	0.011	0.272
8131.4200	Box Making Machine Operator	0.013	0.276
7233.0800	Mechanic, Road Roller	0.015	0.281
8342.0400	Grader Operator	0.016	0.291

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.

Table 37: District-Level Distribution of Baseline Cost-Benefit Results

	Value
Number of districts	95
Mean annual benefit (Rs.)	2,304,925,939
Median annual benefit (Rs.)	1,864,595,530
Mean annual cost, baseline benchmark (Rs.)	361,833,589
Median annual cost, baseline benchmark (Rs.)	158,979,769
Mean district-level benefit-cost ratio	40.538
25th percentile district-level benefit-cost ratio	4.205
Median district-level benefit-cost ratio	10.386
75th percentile district-level benefit-cost ratio	23.806
Mean district-level net benefit (Rs.)	1,943,092,350
Median district-level net benefit (Rs.)	1,670,822,958
Share of districts with positive net benefit	0.937

Notes: Statistics are computed over the 95 districts in the main analysis sample, defined as districts with non-missing population, non-missing wage, non-missing baseline annualized cost, and positive safe tower additions since 2017.

Table 38: Full District-Level Baseline Cost-Benefit Summary

District	State	Added Towers	Benefit (Rs.)	Cost (Rs.)	Net Benefit (Rs.)	BCR
Gopalganj	BIHAR	3	2,242,034,918	5,184,123	2,236,850,795	432.481
Unnao	UTTAR PRADESH	3	1,864,595,530	5,184,123	1,859,411,407	359.674
Muzaffarnagar		3	1,713,713,208	5,184,123	1,708,529,085	330.570
Jhargram	WEST BENGAL	5	2,567,849,854	8,640,205	2,559,209,649	297.198
DevBhumi-Dwarka	GUJARAT	4	1,677,735,122	6,912,164	1,670,822,958	242.722
Pithoragarh	UTTARAKHAND	1	395,526,612	1,728,041	393,798,571	228.887
North East	DELHI	12	3,997,189,378	20,736,492	3,976,452,886	192.761
Darbhanga	BIHAR	10	2,930,496,147	17,280,410	2,913,215,737	169.585
Madhubani	BIHAR	10	2,839,398,889	17,280,410	2,822,118,480	164.313
Mungeli	CHHATTISGARH	5	1,140,923,123	8,640,205	1,132,282,918	132.048
Bhavnagar	GUJARAT	10	1,974,944,973	17,280,410	1,957,664,563	114.288
Siwan	BIHAR	16	2,896,374,607	27,648,655	2,868,725,952	104.756
Anantapur		29	3,268,753,105	50,113,188	3,218,639,917	65.227
Bahraich	UTTAR PRADESH	19	1,911,302,278	32,832,778	1,878,469,499	58.213
Thane		79	7,942,108,862	136,515,236	7,805,593,626	58.177
Janjgir - Champa	CHHATTISGARH	14	1,200,192,399	24,192,574	1,175,999,826	49.610
Y.S.R.		53	3,602,528,903	91,586,171	3,510,942,732	39.335
West Godavari	ANDHRA PRADESH	49	3,213,838,285	84,674,007	3,129,164,278	37.955
Kancheepuram		104	6,497,319,989	179,716,261	6,317,603,728	36.153
Mahe	PUDUCHERRY	2	119,271,915	3,456,082	115,815,833	34.511
Warangal Urban	TELANGANA	59	3,430,223,641	101,954,417	3,328,269,224	33.645
Vellore		76	3,662,070,068	131,331,113	3,530,738,954	27.884
Kurnool		95	4,107,741,587	164,163,892	3,943,577,695	25.022
Ghaziabad		74	3,185,587,093	127,875,032	3,057,712,061	24.912
Visakhapatnam		148	5,805,663,551	255,750,063	5,549,913,488	22.701
Nagarkurnool	TELANGANA	92	3,598,032,946	158,979,769	3,439,053,177	22.632
Saharsa	BIHAR	40	1,553,306,424	69,121,639	1,484,184,786	22.472
Chirang	ASSAM	6	222,185,549	10,368,246	211,817,304	21.429
Vellore		76	2,718,528,976	131,331,113	2,587,197,862	20.700
Chitrakoot	UTTAR PRADESH	18	635,277,315	31,104,737	604,172,578	20.424
Karimnagar	TELANGANA	104	3,481,534,661	179,716,261	3,301,818,400	19.372
Supaul	BIHAR	37	1,224,236,002	63,937,516	1,160,298,487	19.147
Jalpaiguri		66	2,147,118,436	114,050,704	2,033,067,732	18.826
Warangal Rural	TELANGANA	59	1,918,505,072	101,954,417	1,816,550,655	18.817
Shajapur		19	597,443,376	32,832,778	564,610,598	18.197
Bhiwani		41	1,175,821,442	70,849,680	1,104,971,763	16.596
Vaishali	BIHAR	95	2,393,158,818	164,163,892	2,228,994,926	14.578
Rajgarh	MADHYA PRADESH	45	1,118,880,042	77,761,844	1,041,118,198	14.389
Fatehabad	HARYANA	25	617,441,091	43,201,024	574,240,067	14.292

District	State	Added Towers	Benefit (Rs.)	Cost (Rs.)	Net Benefit (Rs.)	BCR
Sitapur	UTTAR PRADESH	76	1,867,232,260	131,331,113	1,735,901,147	14.218
South		147	3,380,169,803	254,022,022	3,126,147,781	13.307
Narayanpet	TELANGANA	251	5,219,812,172	433,738,283	4,786,073,890	12.034
Karimnagar		104	2,037,445,000	179,716,261	1,857,728,739	11.337
East		152	2,921,010,436	262,662,227	2,658,348,209	11.121
Arvalli	GUJARAT	96	1,828,456,895	165,891,933	1,662,564,962	11.022
Raigarh	CHHATTISGARH	48	906,485,986	82,945,966	823,540,020	10.929
Jogulamba Gadwal	TELANGANA	251	4,720,794,978	433,738,283	4,287,056,696	10.884
Barmer	RAJASTHAN	78	1,399,960,873	134,787,195	1,265,173,678	10.386
Subarnapur	ODISHA	16	276,565,246	27,648,655	248,916,591	10.003
Visakhapatnam		148	2,331,272,090	255,750,063	2,075,522,027	9.115
Tapi	GUJARAT	24	370,900,994	41,472,983	329,428,010	8.943
Bargarh	ODISHA	50	763,166,589	86,402,048	676,764,540	8.833
Central	DELHI	68	1,031,808,819	117,506,786	914,302,033	8.781
Mahbubnagar		251	3,337,237,292	433,738,283	2,903,499,009	7.694
Parbhani	MAHARASHTRA	109	1,419,267,555	188,356,465	1,230,911,090	7.535
Gir Somnath	GUJARAT	183	2,268,729,292	316,231,497	1,952,497,796	7.174
Wanaparthy	TELANGANA	251	3,076,952,379	433,738,283	2,643,214,097	7.094
Chittoor		319	3,438,628,783	551,245,068	2,887,383,714	6.238
Hamirpur	UTTAR PRADESH	46	478,396,287	79,489,884	398,906,403	6.018
Paschim Barddhaman	WEST BENGAL	637	6,101,007,208	1,100,762,096	5,000,245,112	5.543
Vikarabad	TELANGANA	601	5,420,596,370	1,038,552,621	4,382,043,749	5.219
Sangareddy	TELANGANA	625	5,361,327,409	1,080,025,604	4,281,301,805	4.964
Hyderabad	TELANGANA	976	8,176,195,983	1,686,567,984	6,489,628,000	4.848
Rangareddy		1,064	8,741,881,193	1,838,635,589	6,903,245,604	4.755
Pratapgarh	RAJASTHAN	84	678,789,354	145,155,441	533,633,912	4.676
Banswara	RAJASTHAN	169	1,320,197,786	292,038,923	1,028,158,862	4.521
Champawat	UTTARAKHAND	21	163,358,822	36,288,860	127,069,962	4.502
Ashoknagar	MADHYA PRADESH	50	388,042,389	86,402,048	301,640,341	4.491
Nalgonda	TELANGANA	443	3,432,367,935	765,522,148	2,666,845,787	4.484
Khammam	TELANGANA	301	2,298,534,240	520,140,331	1,778,393,909	4.419
Mandsaur	MADHYA PRADESH	163	1,185,539,664	281,670,678	903,868,986	4.209
Sultanpur		223	1,618,667,271	385,353,136	1,233,314,136	4.200
Suryapet	TELANGANA	443	3,154,545,676	765,522,148	2,389,023,528	4.121
Amreli	GUJARAT	164	1,119,878,693	283,398,719	836,479,974	3.952
Kalimpong	WEST BENGAL	196	1,264,406,216	338,696,029	925,710,187	3.733
Narmada	GUJARAT	59	357,110,050	101,954,417	255,155,633	3.503
Medchal-Malkajgiri	TELANGANA	1,064	6,226,432,057	1,838,635,589	4,387,796,468	3.386
Jalna	MAHARASHTRA	235	1,353,998,596	406,089,627	947,908,969	3.334
Sheopur	MADHYA PRADESH	68	377,478,526	117,506,786	259,971,741	3.212

District	State	Added Towers	Benefit (Rs.)	Cost (Rs.)	Net Benefit (Rs.)	BCR
Umaria	MADHYA PRADESH	66	363,246,471	114,050,704	249,195,767	3.185
Neemuch	MADHYA PRADESH	119	650,099,001	205,636,875	444,462,126	3.161
Sirsa	HARYANA	167	881,078,562	288,582,841	592,495,720	3.053
Yadadri Bhuvanagiri	TELANGANA	625	3,000,899,392	1,080,025,604	1,920,873,788	2.779
Saraikela-Kharsawan	JHARKHAND	175	696,824,042	302,407,169	394,416,873	2.304
Medak	TELANGANA	625	2,264,583,543	1,080,025,604	1,184,557,939	2.097
Chandrapur	MAHARASHTRA	491	1,685,524,235	848,468,115	837,056,121	1.987
Kathua	JAMMU & KASHMIR	189	545,964,859	326,599,743	219,365,117	1.672
Vadodara		1,175	3,226,263,860	2,030,448,136	1,195,815,724	1.589
Siddipet	TELANGANA	625	1,641,613,623	1,080,025,604	561,588,018	1.520
Leh(Ladakh)		120	199,430,769	207,364,916	-7,934,147	0.962
Kamareddy	TELANGANA	994	1,649,557,702	1,717,672,721	-68,115,019	0.960
Shivpuri	MADHYA PRADESH	318	447,611,255	549,517,027	-101,905,772	0.815
Balangir	ODISHA	1,053	1,170,828,840	1,819,627,138	-648,798,298	0.643
Malkangiri	ODISHA	251	275,521,389	433,738,283	-158,216,893	0.635
Navsari	GUJARAT	1,039	865,413,268	1,795,434,565	-930,021,296	0.482