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Rewiring Gender Norms: Causal Evidence on Internet Exposure and Justification of Intimate Partner Violence

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Abstract

This paper evaluates the causal impact of women's exposure to the internet on their attitudes towards intimate partner violence (IPV) using data from the most recent round of the National Family Health Survey (NFHS-5). To address potential endogeneity, we exploit exogenous variation in district-level mobile tower density in India as an instrument for women's internet exposure. The instrumental variables estimation provides robust evidence that a woman's exposure to internet reduces her likelihood of justifying IPV by 21 percentage points. We also provide suggestive evidence that higher awareness and physical mobility are potential mechanisms through which internet exposure shapes attitudes. Our findings highlight the transformative potential of digital connectivity in challenging regressive gender norms.

JEL Classifications: C26, J12, J16, I30, O12

Keywords: Internet Exposure, Tower Density, Intimate Partner Violence, Attitudes, Instrumental Variable, NFHS, India

Ordering of authors: The order of authors' names has been determined through randomization. All authors have contributed equally and significantly to this manuscript.

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1 Introduction

Digital technologies are increasingly central to the economic and social lives of people in the developing world, influencing how they access information, public services and markets. This digital transformation rests critically on internet connectivity, which is crucial for building well-functioning digital economies that can help countries achieve sustainable economic growth and productivity (World Bank Group, 2023). India offers a particularly salient case of digital transformation. Over the past decade, access to mobile services has expanded dramatically, with estimates suggesting almost 1174 million telephone subscribers in 2020 (Telecom Regulatory Authority of India, 2021). The spread of Information and Communication Technologies (ICT), especially mobile internet, has connected large parts of the population into digital networks, including rural India and previously underserved areas. As of 2023, India had over 800 million internet users, with rural internet penetration growing faster than in urban areas (Telecom Regulatory Authority of India, 2024a). This digital footprint has brought new opportunities for access to services, information, markets, and civic participation, particularly for women (Donati, 2023). Several studies have documented the individual-level benefits of internet expansion, like improvements in employment (Azam et al., 2024; Bahia et al., 2024; Jain and Chatterjee, 2024), entrepreneurship (Mishra and Mohanty, 2022), age at marriage (Zhang et al., 2023; Murray, 2020), contraceptive use (Toffolutti et al., 2020), intimate partner violence (Dhamija et al., 2025a), maternal and reproductive health outcomes (Krishnatri and Vellakkal, 2024), and dietary diversity (Vatsa et al., 2023; Deng et al., 2024). However, the impact of this digital footprint on gendered social outcomes, for instance, women's beliefs, attitudes, and normative frameworks within the household, remains understudied.

India remains one of the most gender-unequal societies globally (World Economic Forum, 2025), where patriarchal structures and gender norms "inhibit women from asserting their rights, exercising agency, and making choices about various aspects of their lives, spanning from marriage and childbearing to freedom of expression and movement" (Jejeebhoy, 2024) (page 2). Social norms that justify intimate partner violence (IPV) are widespread and embedded in household and community life. The National Family Health Survey (2019–21) data show that nearly 30% of ever-married women have experienced physical or sexual violence and 43% of women themselves continue to justify wife-beating under certain circumstances. Such internalization of patriarchal norms not only perpetuates violence but also hinders women's ability to seek help or resist oppression (Shreemoyee et al., 2025; Dhamija et al., 2024; Simon et al., 2001; Jewkes, 2002; Johnson and Das, 2009; Hindin, 2003; Mookerjee et al., 2021; Gage and Hutchinson, 2006). In this vein, understanding how internet utilization can transform such

norms is critical from a policy perspective to address gender-based violence.

Internet exposure has the potential to expand women's access to new ideas, role models, networks, and information. Prior research shows that impartial social networks and non-conformist ideas accessed through modern media and education can challenge deeply entrenched social norms (Rani et al., 2004). Yet, women's access to digital opportunities in India remains constrained by the digital gender divide.[1] With relatively limited affordability, literacy, and digital skills, women additionally face gender-specific barriers rooted in discriminatory socio-cultural norms.[2] Kumawat and Garg (2025) observes, "use of technology is gendered, as in the hands of women, technology is seen as an object of distrust and must be monitored to comply with social and cultural norms."(page 976). Such normative pressures instil fear, insecurity, and hesitation among women, limiting their digital engagement. Therefore, increased digital exposure for women carries immense potential to affect internalized patriarchal attitudes, challenge regressive social norms and reshape ones' beliefs. Yet, rigorous causal evidence on whether internet exposure transforms women's gendered attitudes remains scarce. Addressing this gap, our paper examines the causal effect of women's internet exposure on their attitudes towards IPV.

For our analysis, we use individual-level data from the latest round of the National Family Health Survey (NFHS-5), which includes rich information on women's internet use and their attitudes toward IPV. We utilize an Instrumental Variable approach to identify the causal effect of digital exposure on the probability of women justifying wife-beating attitudes, while addressing concerns of endogenous selection into internet use. Specifically, we exploit the exogenous variation in India's mobile internet infrastructure, measured by district-level mobile tower density, as an instrument for women's internet exposure.

Our findings are noteworthy. We find that internet exposure leads to a statistically significant and substantial reduction in women's justification of IPV. These results are robust to a wide set of controls, alternative specifications of both the exposure and outcome variables, and falsification tests. Sub-sample analyses reveal that the effect holds across caste, class, education, and geography, with particularly strong effects among women in non-poor households, with lower education, and in urban areas. We also explore mechanisms and provide suggestive evidence on how internet exposure shapes women's IPV attitudes. Our findings indicate that internet use increases women's awareness and enhances their freedom of movement, thereby

[1] The Comprehensive Modular Survey: Telecom, 2025 (Ministry of Statistics and Programme Implementation and National Statistics Office, 2025) reports that only 63.1% of women used the internet in the past three months, compared to 76.7% of men.

[2] Phones and the internet are often seen as a bad influence on girls, leading to explicit restrictions on their use (Dhawan, 2023).

exposing them to alternative narratives around gender and violence.

This work contributes to three main strands of literature. First, we add to the burgeoning literature that examines the role of internet in shaping attitudes in general (Golin and Romarri, 2024; Zhang et al., 2025; Zhou et al., 2020; Liu et al., 2021; Chai et al., 2025; Li et al., 2024; Chong et al., 2020). Second, our paper also contributes to the growing literature that looks at the effects of media, in general, and internet connectivity, in particular, on various dimensions of socioeconomic outcomes, including test scores (Gentzkow and Shapiro, 2008), mental health (Arenas-Arroyo et al., 2025; Golin, 2022), body weight (DiNardi et al., 2019; Golin, 2022), consumption (Bahia et al., 2023), labour market outcomes (Akerman et al., 2015; Atasoy, 2013; Dettling, 2017; Kolko, 2012; Azam et al., 2024; Viollaz and Winkler, 2022; Chiplunkar and Goldberg, 2022), age at marriage (Zhang et al., 2023), marital market matching (Bellou, 2015; Potarca, 2017), intimate partner violence (Dhamija et al., 2025a), and fertility (Jensen and Oster, 2009; Ferrara et al., 2012; Kearney and Levine, 2015; Guldi and Herbst, 2017; Billari et al., 2019). Finally, our work relates to the broader literature that examines various possible determinants of attitudes towards IPV including primary education (Deschênes and Hotte, 2024), neighbourhood attitudes (Dhamija et al., 2024), and urbanization (Dhamija et al., 2025b) among others.[3]

By showing that internet exposure can act as a catalyst for individuals to reshape their beliefs that support regressive norms about what is (is not) acceptable behaviour, we offer a new perspective on the effects of digital transformation in the country. Digital infrastructure can be exploited as a tool for social change by specifically addressing attitudes that perpetuate violence against women. As India continues to deepen its digital infrastructure, ensuring that women are not just connected, but empowered through digital exposure, is critical to advancing gender justice.

2 Evolution of Internet in India

India's internet journey began in the 1980s with institutional networks developed for academic and government users. In 1986, the Education and Research Network (ERNET) was launched with support from the United Nations Development Programme to serve universities and research institutions (Vinayak, 2020). Early access remained restricted to academic and scientific communities through ERNET and the National Informatics Centre Network (NICNET), with no provision for public use. Public access arrived only in August 1995, when the state-run telecom company Videsh Sanchar Nigam Limited (VSNL) introduced its internet ser-

[3]For a comprehensive review of factors influencing attitudes toward IPV please refer to Wang (2016).

vices (Vinayak, 2020; ET Online, 2020). Initially, availability was confined to the four largest cities of Delhi, Mumbai, Chennai, and Kolkata. Growth remained slow even after private firms entered in 1998, constrained by high costs, slow speeds, and weak infrastructure. Third Generation (3G) services launched in 2008 also failed to attract mass adoption. Internet subscribers (broadband and dial-up combined) numbered only 0.95 million in the late 1990s and rose to just 11.1 million by 2008 (Mangla and Singh, 2021). As late as 2015, two-thirds of wireless users still relied on Second Generation (2G) services (Telecom Regulatory Authority of India, 2019).

The government's Digital India programme, introduced in 2015, was designed to scale up and broaden the country's modest levels of internet penetration (TOI Business Desk, 2025). A transformative shift occurred in September 2016 with the entry of Reliance Jio. By offering free voice calls and ultra-low-cost 4G data, Jio sparked a price war. Within three quarters, average data prices fell by over 90%, from USD 3 per gigabyte in Q2 2016 to USD 0.30 in Q1 2017 (Krishnatri and Vellakkal, 2024). As a result, internet use surged. According to the Telecom Regulatory Authority of India (Telecom Regulatory Authority of India, 2016), internet subscriptions in India rose from approximately 367.48 million in mid-2016 to 829.30 million in December 2021. By late 2021, India counted 801.58 million subscribers who accessed the internet via mobile devices, underscoring the dominance of wireless connectivity (Telecom Regulatory Authority of India, 2022). Market concentration was also notable, with Reliance Jio holding 421.05 million broadband subscribers, followed by Bharti Airtel (361.35 million), Vodafone Idea (266.05 million), and BSNL (121.95 million) (Telecom Regulatory Authority of India, 2022). Given this overwhelming reliance on wireless services, the presence and density of cell towers became the key determinant of internet availability across regions.

The expansion of towers was initially slow because operators had to build and maintain their own infrastructure, leading them to focus on profitable urban markets and leaving rural districts underserved. The introduction of the *Towerco model* radically altered the functioning of the telecom infrastructure market (Azam et al., 2024). Under this model, independent firms build and manage towers that operators rent and share to lower costs and expand coverage quickly. The effect was dramatic, with the number of base stations rising from 0.18 in 2008 to over 22 million in 2020, while the number of macro towers grew from 0.25 million in 2007 to more than 0.61 million in 2020 (Azam et al., 2024). Business-friendly policies with no licensing or access restrictions further encouraged growth and, by 2020, Towercos managed 84% of India's towers (Houngbonon et al., 2021). The Towerco model also facilitated expansion into less profitable rural areas. Reliance Jio's swift market entry demonstrates this. In 2014, it partnered with Indus Towers to share over 0.11 million towers, allowing it to operate in 15 of India's 22 telecom

circles without building new infrastructure. By 2020, Jio had installed 0.13 million of its own 4G towers and achieved coverage across almost the whole country, including areas with irregular supply of electricity (Azam et al., 2024).

3 Data

This study utilizes the fifth round of NFHS (International Institute for Population Sciences (IIPS) and ICF, 2021) conducted in India during 2019-21. The NFHS is a nationally representative, cross-sectional demographic health survey, forming part of the global Demographic and Health Survey (DHS) program.[4] In India, 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.[5]

A separate women's questionnaire was administered to all eligible women aged 15–49 residing in 636,669 sampled households. The woman's questionnaire included questions on a wide range of domains central to gender and household dynamics, including demographic background, fertility and family planning, nutrition, marriage, sexual activity, employment, domestic violence, mobility, and autonomy. However, questions on certain topics such as attitudes towards IPV were included only for a randomly selected subsample of approximately 15 percent of households through the state module.

3.1 IPV attitudes

Our primary outcome variable captures women's attitudes toward IPV. Specifically, respondents were asked whether a husband is justified in beating his wife under the following circumstances: *(1) if the wife goes out without telling her husband, (2) neglects children, (3) argues with husband, (4) refuses sex, (5) does not cook food properly, (6) is unfaithful, and (7) is disrespectful.* We code each response as 1 if the respondent considered violence *justified* and 0 otherwise. Following prior literature (Shreemoyee et al., 2025; Dhamija et al., 2024), we construct a binary variable of acceptability of IPV, $IPV\,Attitudes$, such that it takes the value 1 if a woman justifies wife-beating in at least one of these situations and 0 otherwise.

[4]The DHS surveys for all countries are available at https://dhsprogram.com/.

[5]See International Institute for Population Sciences (IIPS) and ICF (2021) for more details on the survey methodology.

3.2 Variable of interest and other controls

Our main explanatory variable of interest is women's exposure to the internet, denoted as *InternetExposure*. It takes the value 1 if a woman has ever used the internet and 0 otherwise. Additionally, we include a range of control variables to account for potential confounding variables (Oster, 2019) that might bias the relationship between internet exposure and women's attitudes toward IPV. These include women's characteristics, household characteristics, district-level socioeconomic characteristics, and geographical characteristics.

Women's characteristics include woman's age (in years), education (in completed years), employed during the last twelve months (yes/no), duration of residence in current location (in years), current marital status (yes/no/never in union), exposure to mass-media (yes/no), house or land ownership (yes/no). Household level characteristics include male-headed household (yes/no), age of the head (in years), number of household members, religion (Hindu/Muslim/others), social group (Scheduled Caste/Scheduled Tribe/Other Backward Class/others/missing)[6], wealth category (poor/non-poor), and indicator for the area of residence (rural/urban).

The set of district-level socioeconomic characteristics comprises the following variables: number of primary, middle, and secondary schools, as well as medical, engineering, arts and science, vocational training colleges, family welfare centres, maternity and child welfare centres, sex ratio (female/male), and percentage of SC/ST population. These characteristics are available in the district census abstract of 2011 Indian Census.[7]

The geographical controls capture ecological and infrastructural variation that may indirectly shape both internet access and attitudes, including elevation, ruggedness, nighttime lights intensity, annual number of days with lightning, and vegetation continuous fields. Elevation data is available in Shuttle Radar Topography Mission (SRTM) at 1-arc second resolution. Ruggedness measure the elevation difference between two surfaces (Nunn and Puga, 2012; Riley et al., 1999). Nighttime lights, as a proxy for local economic development and urbanization (Dhamija et al., 2025b), are measured in average cloud-free radiance values (Mayala et al., 2018; Mayala and Donohue, 2022).[8] The total number of days with lightning shocks are available in India Meteorological Department's Annual Disaster Weather Report, 1969–2019.[9] We transform these variables into their natural logarithmic form to reduce the influence of extreme outliers.

[6]Scheduled Castes are referred to as SC, Scheduled Tribes as ST, and Other Backward Castes as OBC throughout the manuscript.

[7]The district census abstract provides the aggregated number of schools in all the villages and towns of a district.

[8]They are drawn from annual nighttime light intensity data (provided as raster surfaces) measured by the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB), flown jointly by National Aeronautics and Space Administration (NASA) and National Oceanic and Atmospheric Administration (NOAA) (Elvidge et al., 2017).

[9]For more details, see - https://imdpune.gov.in/hazardatlas/lightvulabout.html

Vegetation continuous fields capture annual tree cover in the form of the percentage of each pixel under forest cover.[10] Moreover, we use one-year lagged nighttime lights and vegetation continuous fields for each district surveyed during 2019-21.

We draw district-level socioeconomic characteristics and geographical characteristics from the Socioeconomic High-resolution Rural-Urban Geographic Platform for India (SHRUG), an open-access database that documents multidimensional development across more than 600,000 villages and towns in India.[11] NFHS-5 data are matched to SHRUG indicators at the district level, with complete information available for 692 districts.

3.3 Instrument Variable

Our instrument variable, district-level mobile tower density, is drawn from OpenCellID. The dataset is an open-access and partially crowd-sourced repository of cellular tower locations.[12] It provides the latitude and longitude of Base Transceiver Stations (BTS). As of August 18, 2020, the database recorded 2.26 million BTS in India. We downloaded the BTS location data for India and linked them to NFHS districts using the DHS district shapefile. Tower density is then calculated as the number of BTS in a district divided by its geographical area. In line with other geographical characteristics, we use natural logarithmic of tower density after adding one to it. For brevity, we refer to our instrumental variable, $log(1 + TowerDensity)$, as $AdjustedTowerDensity$ throughout the paper.

3.4 Analytical Sample

We use the individual recode file of NFHS-5, which contains one record for each eligible woman respondent. The state module comprises 108,785 women between the ages of 15 and 49 years. We construct our analytical sample in two steps. First, we exclude 2,817 women who were reported as visitors in the household, retaining only usual residents. This reduces the sample to 105,968 observations. Second, we restrict the sample to women with complete information on the outcome, treatment, instrumental variable, and other explanatory variables. After accounting for missing values, our final analytical sample consists of 102,203 women. Specifically, we drop missing observations in the outcome variable (1,484), number of years a woman has resided at present location (107), age of household head (17), socioeconomic characteristics (2,157). Figure A1 provides a schematic overview of this sample construction.

[10] This is generated from a machine learning model based on a combination of images from NASA MODIS and samples from higher resolution satellites (Townshend et al., 2011).

[11] The SHRUG is an open data platform available at http://devdatalab.org/shrug. See (Asher et al., 2021) for more details.

[12] Avaliable at https://datacatalog.worldbank.org/search/dataset/0038043/Global-OpenCellID-cell-tower-map. Additional details are available at https://www.opencellid.org/

3.5 Descriptive Statistics

Table 1 presents summary statistics for woman- and household-level characteristics. In our analytical sample, 43% of the women, on average, justify IPV. The average respondent is 30.6 years old, with 7.4 years of completed education. Around 33% of women report having used the internet, 32% are employed, 71% are currently married, 76% report some exposure to mass media, and 47% own land or a house. On average, women have resided in their current location for about 15.9 years.

At the household level, 84% of households have male heads, with an average age of 48.2 years, and 5.3 members. The religious composition shows that 75% of households are Hindu, 13% Muslim, and 12% belong to other religions. Social group composition is diverse, with 19% belonging to Scheduled Castes, 19% to Scheduled Tribes, 39% to Other Backward Classes, and 18% to other social categories. Around, 43% of the households in our analytical sample fall in the poorest and poor category in terms of wealth index.[13] Approximately three-quarters (75%) of the sample resides in rural areas.

Table 2 provides summary statistics of district-level characteristics. In 2011, districts on average had 1,629 primary schools, 743 middle schools, and 327 secondary schools. In terms of higher and technical education, districts had on average 2 medical colleges, 6 engineering colleges, 15 arts and science colleges, and 14 vocational training institutes. Health infrastructure included an average of 64 maternity and child welfare centres and 107 family welfare centres per district. District populations were on average 33% SC/ST, and the sex ratio was 947 females per 1000 males. In our analytical sample, the average number of towers and tower density are 3123.51 and 3.07, respectively. Figure 1 illustrates the spatial distribution of tower density. The distribution of $AdjustedTowerDensity$, log transformation of tower density, is presented in Figure 2.

[13]The DHS wealth index is a standardized measure of household economic status that classifies households into five groups: poorest, poor, middle, richer, and richest.

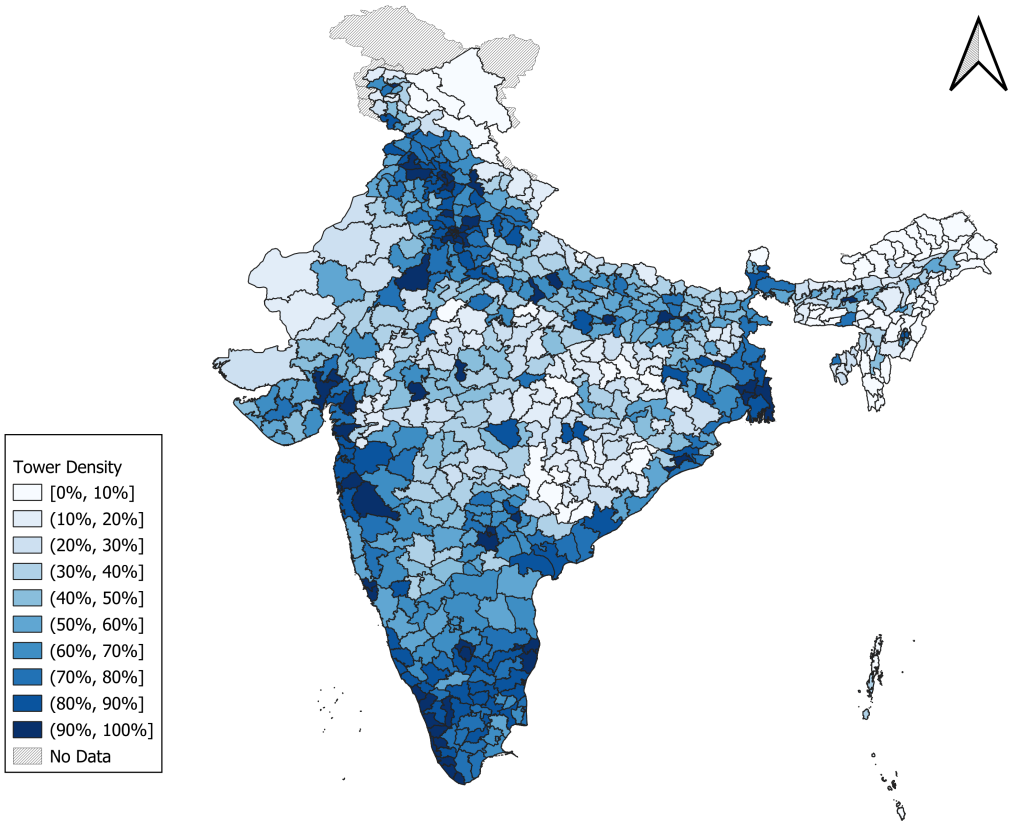

Figure 1: District level distribution of tower density.

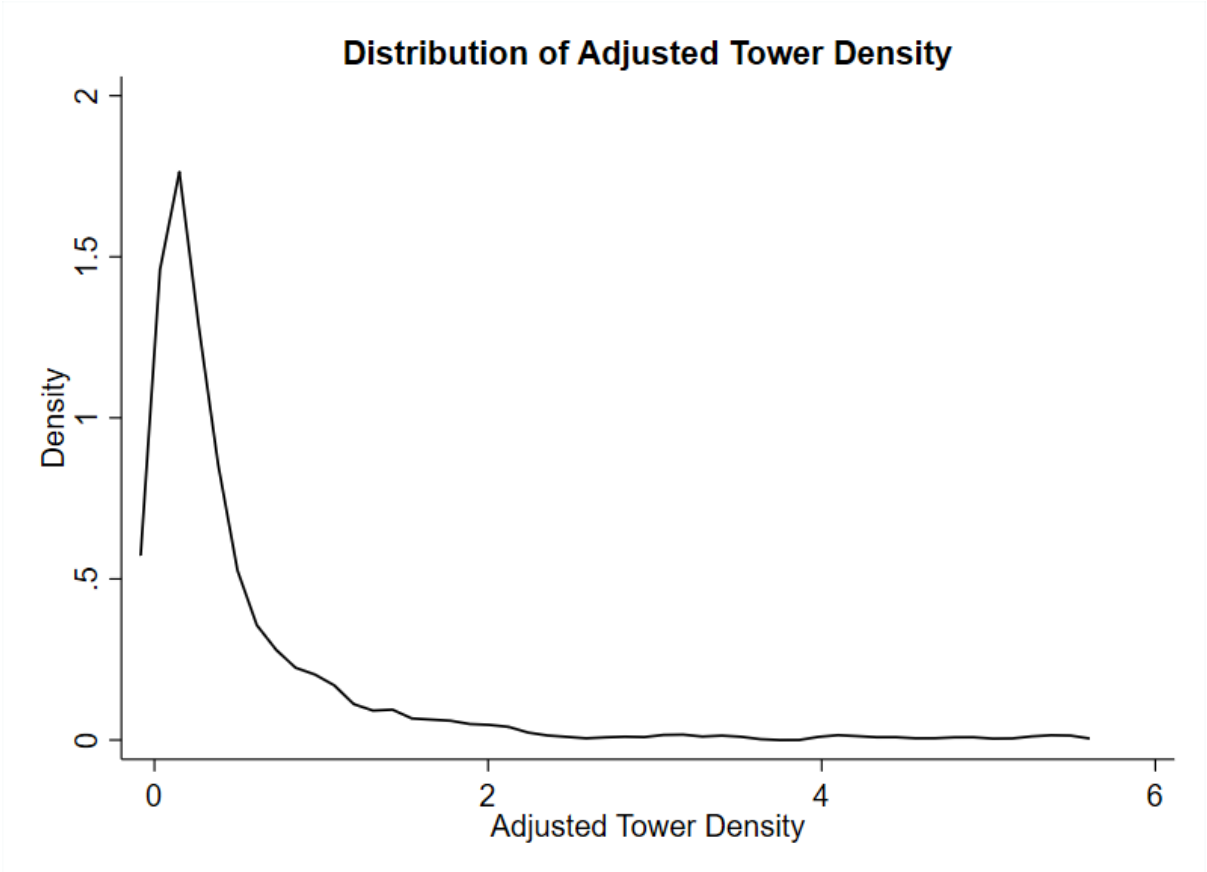

Figure 2: Kernel density plot of adjusted tower density.

4 Empirical framework

4.1 Estimation strategy

We use the following empirical specification to investigate the effect of women's exposure to the internet on their attitudes justifying IPV:

$$IPVAttitudes_i = \beta_0 + \beta_1 InternetExposure_i + \beta_2 \mathbb{X}_{ih} + \beta_3 \mathbb{G}_d + \beta_4 (\mathbb{S}_d \times t) + \theta_s + \epsilon_{ihdst} \quad (1)$$

where $IPVAttitudes_i$ refers to the outcome of interest for woman i; $InternetExposure_i$ denotes the woman i's exposure to internet; $\mathbb{X}_{ih}$ is the vector of woman level and household level characteristics; $\mathbb{G}_d$ is the vector of geographic characteristics of her district of residence; $\mathbb{S}_d$ is the vector of other socioeconomic characteristics of the districts as per the 2011 census interacted with survey year t; θ_s are the state fixed effects and ϵ_{ihdst} is the idiosyncratic error term. All standard errors are clustered at the cluster level.

Our coefficient of interest, β_1, captures the effect of women's internet exposure on their attitudes towards IPV. A causal interpretation of β_1 requires that no unobserved variables are simultaneously correlated with both our variable of interest and outcome variable, conditional on the included controls. If such endogeneity exists, ordinary least squares (OLS) estimate of β_1 would be biased and inconsistent. For instance, patriarchal norms may restrict women's external exposure, including access to and use of the internet, now a critical tool for information and social networking. Simultaneously, these very norms also shape women's attitudes toward IPV, reinforcing the internalization of gender hierarchies (Shreemoyee et al., 2025; Dhamija et al., 2024).

Our specification addresses these concerns through multiple layers of controls. First, the inclusion of state fixed effects accounts for time-invariant state-level unobservables that may affect both internet exposure and IPV attitudes, such as economic structures, colonial-era institutions, missionary activity, and long-standing political conditions. Second, by interacting district-level socioeconomic characteristics with survey year, we capture the influence of initial social and economic conditions at the district level that may differentially shape women's internet exposure and attitudes over time. Third, incorporating district-level geographic characteristics allows us to net out the role of ecological and infrastructural conditions, such as terrain and ruggedness, that directly influence the feasibility of extending internet infrastructure. However, despite these efforts, we admit that concerns regarding omitted variables and measurement error cannot be fully ruled out. Thus, we follow an Instrumental Variable (IV) estimation strategy to alleviate such concerns and estimate the causal effect of a woman's exposure to the internet

on her attitudes towards IPV.

The choice of our instrument, district-level adjusted tower density, is motivated by the structural characteristics of internet access in India. Unlike many high-income countries where fixed broadband penetration is quite common (International Telecommunication Union, 2024), the dominant mode of internet access is through mobile phones in India. In March 2023, over 96% of India's 881.25 million internet subscribers accessed the internet through mobile devices (Telecom Regulatory Authority of India, 2024b). Given the reliance of internet and phone access on wireless technology, the presence and density of cell towers in a location play a crucial role in determining internet availability (Azam et al., 2024). Moreover, access to mobile phone and hence internet has expanded dramatically over the past two decades due to a sharp decline in mobile handset prices, internet data prices, and a massive rollout of mobile phone towers (IANS, 2019; Kar, 2022; Chethan Kumar, 2021; PTI, 2025a).[14] By 2020, tower networks had effectively covered the entire country, including villages that were not yet connected to electricity grids (Purnell, 2018).

Women's access to mobile phones and the internet has been shaped by affordability, technological skills, and restrictive gender norms (Bhargava, 2023; GSMA, 2025; Dhawan, 2023; Kumawat and Garg, 2025). Tower expansion, however, represents a supply-side factor beyond women's individual or household-level choices. Higher density of towers increases signal reliability, efficiency and lowers the marginal cost of mobile data provision, thereby making internet access more feasible (Strusani et al., 2020). Mobile towers are placed largely in response to national coverage mandates and telecom firms' expansion strategies (Dipak K Dash, 2023; PTI, 2018; IANS, 2025; PTI, 2025b; Abbas, 2021), and not based on women's empowerment or household dynamics. This makes it particularly relevant in our context, as it allows us to study the exogenous variation in internet access driven by infrastructure. The following section provides a detailed discussion of our IV strategy:

4.2 Instrumental variable estimation

We estimate a two-stage IV model, which is specified as follows:

$$InternetExposure_i = \alpha_0 + \alpha_1 AdjustedTowerDensity_d + \alpha_2 \mathbb{X}_{ih} + \alpha_3 \mathbb{G}_d + \alpha_4(\mathbb{S}_d \times t) + \phi_s + \eta_{ihdst} \tag{2}$$

[14] For more details on the evolution of teledensity and mobile phone subscriptions in India, see Mangla and Singh (2021) and Telecom Regulatory Authority of India and National Council of Applied Economic Research (2012)

$$IPV\,Attitudes_i = \beta_0 + \beta_1 InternetExposure_i + \beta_2 \mathbb{X}_{ih} + \beta_3 \mathbb{G}_d + \beta_4 (\mathbb{S}_d \times t) + \theta_s + \epsilon_{ihdst} \quad (3)$$

The first stage is given by Equation (2), and Equation (3) is the structural equation. A woman's internet exposure, $InternetExposure_i$, is instrumented by the district-level adjusted tower density. As above, $\mathbb{X}_{ih}$, $\mathbb{G}_d$, and $\mathbb{S}_d \times t$ are the vectors of woman/household level characteristics, district level geographic characteristics, and district level socioeconomic characteristics interacted with survey year t, respectively. ϕ_s or θ_s denote state fixed effects. Our parameter of interest, β_1 captures the effect of woman's internet exposure on her attitudes justifying IPV.

Following the prior literature (Babbar and Ojha, 2024; Gershenson et al., 2022; Chowdhury et al., 2018; Trinh, 2020; Addison and Teixeira, 2019), we use Roodman (2011)'s conditional mixed-processes (CMP) framework as our outcome and variable of interest are binary in nature. The CMP model exploits the limited nature of the first-stage dependent variable and is likely to be more efficient than linear models (Roodman, 2011). Roodman (2011) further notes that CMP is fundamentally a seemingly unrelated regression (SUR) estimation program and can be applied to a broad range of simultaneous equation systems. In this context, CMP serves as a limited-information maximum likelihood (LIML) estimator, with only the coefficients from the final stage carrying structural interpretation. The general likelihood function for such models is provided in Roodman (2011).

4.3 Validity of the IV

In this section, we examine whether adjusted tower density can be used as a valid instrument for women's exposure to internet. First, we plot the district level average of women's internet exposure with adjusted tower density. Figure 3 shows a strong positive correlation between our IV and main variable of interest. Second, Table 3 presents our first-stage results based on Equation (2). Column (1) captures the relationship between women's internet exposure and adjusted tower density without including any controls. The logarithmic transformation of tower density as our IV simplifies interpretation. We find that a 1% change in the district tower density is associated with 11 percentage point (pp) increase in women's likelihood of using the internet. As we move from columns (2) to (4), we subsequently extend the set of controls to include women and household level characteristics in column (2), geographic and socioeconomic district level characteristics in column (3), and state fixed effects in column (4). Across all specifications, we find a robust, strong, positive and statistically significant

relationship between the adjusted tower density and internet exposure of women. Column (4) presents our most preferred specification including the comprehensive set of controls and state fixed effects. We document that a 1% increase in tower density within the district is associated with a 7 pp increase in the probability of the women having internet exposure. The IV does remarkably well on the weak identification and the first stage F tests, with the Kleibergen and Paap rk-LM statistic of 54.01 and the latter, 54.32, respectively in the final specification. This allows us to reject the null that the instrument is uncorrelated with the endogenous regressor. The first stage F statistic is well above 10 across all specifications, suggesting an absence of a weak-instrument problem.

Third, we argue that our instrument, adjusted tower density, does not have a direct impact on our outcome variable, a woman's attitudes towards IPV, conditional on covariates included in the IV regression model. For instance, it is possible that socioeconomic structure of a district might affect the district level adjusted tower density. The correlation between district level socioeconomic characteristics and adjusted tower density is likely to be stronger when the telecom operators have to build their own towers, and thus they enter into only the high profit areas to recover their fixed costs (Azam et al., 2024). Moreover, these district level socioeconomic characteristics could potentially be correlated with women's attitudes towards IPV (Jesmin, 2017; Boyle et al., 2009; Sardinha and Catalán, 2018). This would violate the exclusion restriction, as the adjusted tower density could also directly affect women's attitudes towards IPV.

We use a twofold approach to alleviate these concerns. First, we include a rich set of covariates capturing both geographic and socioeconomic characteristics, along with state fixed effects. Second, we conduct a residual-based check to visually assess the relationship between the outcome and the instrument. Specifically, we regress attitudes towards IPV on internet exposure and obtain the residuals, and similarly obtain the residuals from regressing adjusted tower density on internet exposure. Figure 4 plots these residuals and reveals no discernible pattern or association, reinforcing our claim that, conditional on internet exposure, adjusted tower density is unrelated to attitudes towards IPV.

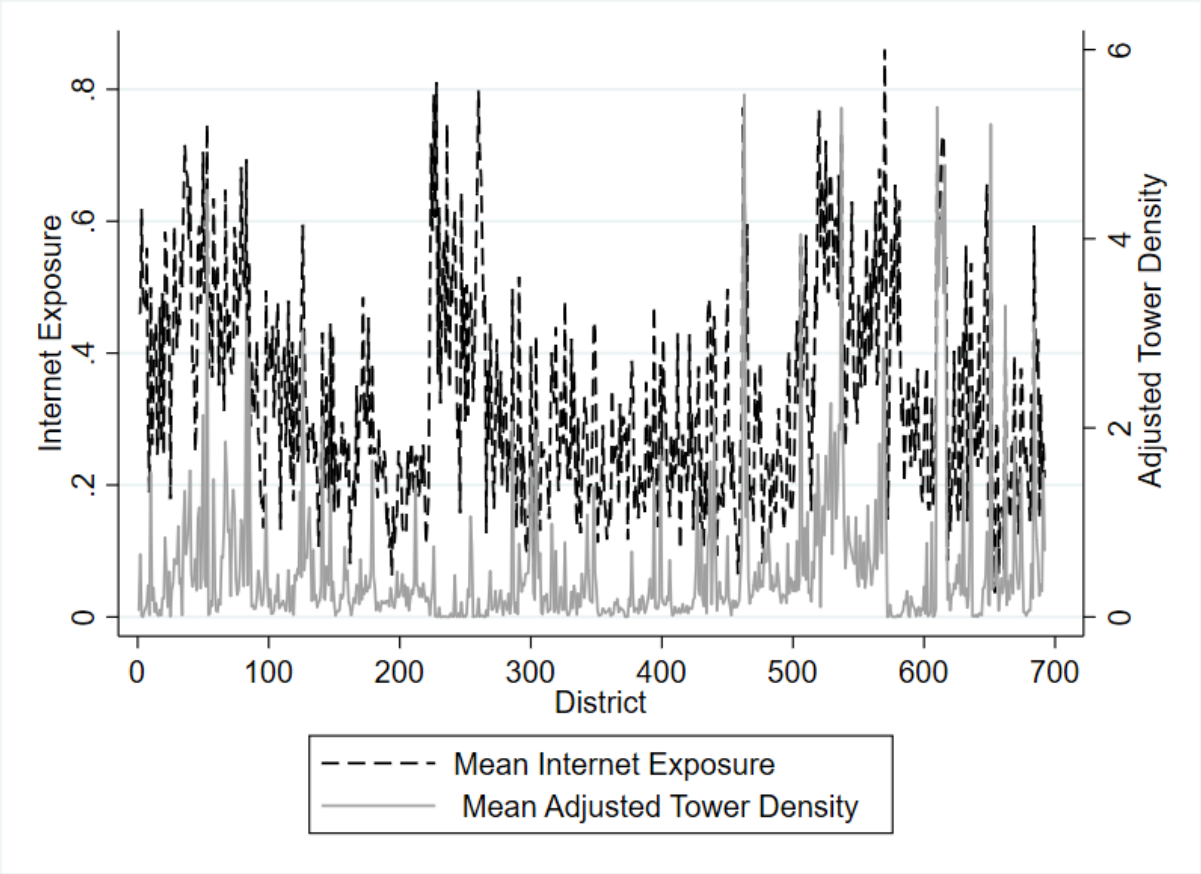

Figure 3: First stage correlation between average district level internet exposure and district level adjusted tower density

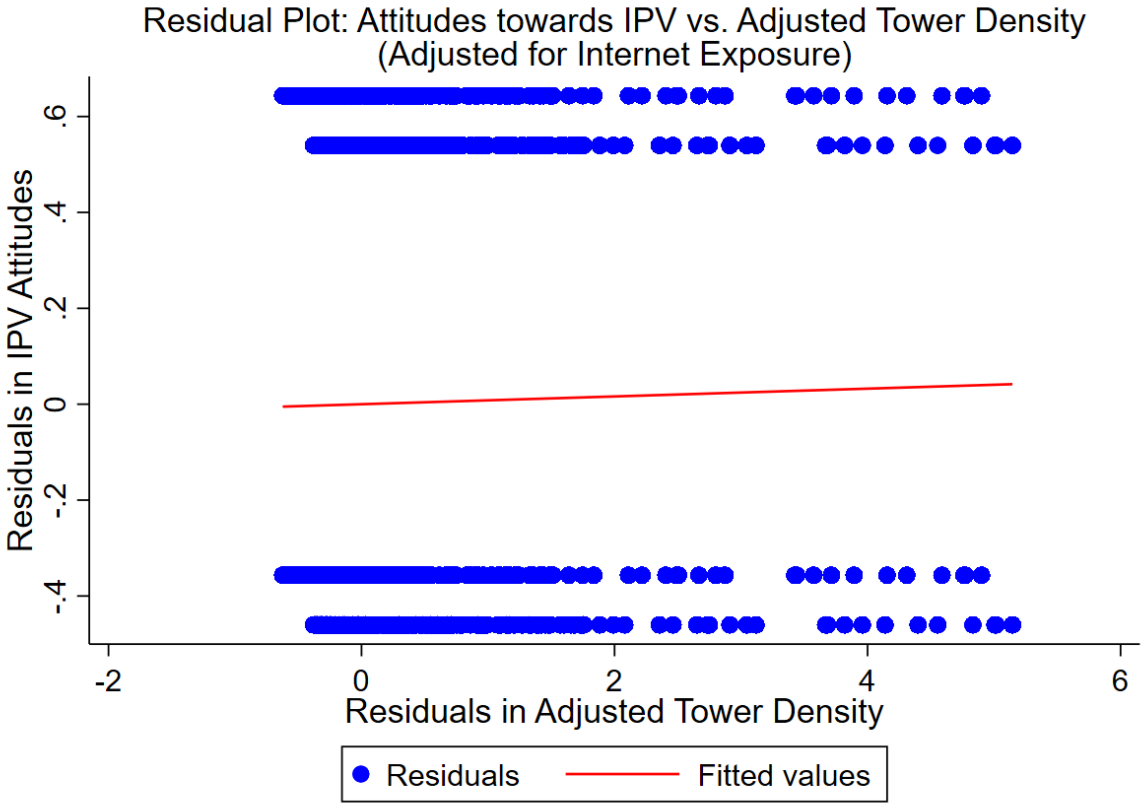

Figure 4: Residual plots: Attitude towards IPV vs Adjusted Tower Density

5 Results

5.1 Baseline results

We present the baseline results in Table 4. Given that the dependent variable is binary in nature, we present the baseline results from a Probit estimation in panel A, columns (1)–(4). Column (1) presents estimates from a naive specification where we regress IPV attitudes on the woman's exposure to the internet. We find a negative association between them. As we move to columns (2) and (3), we subsequently add the set of women and household level, and geographic and sociodemographic level characteristics respectively. Column (4) is the Probit specification with all relevant controls including state fixed effects, and we find that a woman's exposure to internet is associated with a reduction in her acceptance of IPV by 5 pp.

In panel B, we present the marginal effects from the IV estimation in the same progression as in panel A. As we move from column (5) to (6), we add women and household level characteristics; and as we move to columns (7) and (8), we subsequently add the district level geographic, socioeconomic characteristics, and state fixed effects to our specifications respectively. Across columns (6) to (8), we find a negative and significant effect of a woman's internet exposure on

her attitudes justifying IPV. Our most preferred specification is in column (8) with the entire set of comprehensive controls and state fixed effects. We find that a woman's exposure to internet reduces her likelihood of justifying IPV by 21 pp. The effect is statistically significant at 1% significance level. This shows a sizable causal relationship reflecting that digital connectivity serves as a significant lever in shifting women's perceptions of gender norms and reducing their acceptance of IPV.

6 Potential mechanism

To examine the mechanisms supporting the negative and statistically significant effect of women's internet exposure on their attitudes towards IPV, we first explore whether increased awareness acts as a potential channel. Internet exposure likely enhances women's general awareness and information exposure through greater connectivity with their networks or peer interactions, which may shift attitudes around patriarchal norms and domestic violence. Extant literature documents evidence that the internet is closely linked with women's awareness about healthcare amongst others (Pandey et al., 2003; Meherali et al., 2021; Pickard et al., 2024). To empirically test whether awareness is a channel, we first study the relationship between internet exposure and women's awareness. We utilize the NFHS-5 data on whether or not women have heard about AIDS, family planning, or both through the internet. We construct the binary indicator for awareness as taking the value 1 if the response is yes to any of these and 0 otherwise.

Table 5, Panel A presents the results. First, we run an IV estimation to capture the effect of internet exposure on women's awareness instrumented by adjusted tower density in the districts. Column (1) shows that woman's internet exposure significantly increases her likelihood of awareness by 24 pp. Subsequently, using the methodology followed by (Mookerjee et al., 2023; Bose et al., 2020), we generate predicted values of awareness, which we then use in a simple linear regression to explain a change in a woman's attitudes towards IPV. Given that we use a generated regressor, we bootstrap the standard errors with 100 replications to avoid the generated regressor problem. We find that awareness is significantly and negatively associated with the likelihood of justifying IPV. These findings provide supporting evidence that greater awareness is indeed a mechanism through which internet exposure reshapes women's gendered attitudes, reducing their justification of IPV.

In a similar vein, we examine whether women's freedom of mobility serves as an additional mechanism that explains the negative effect of internet exposure on acceptance of IPV. In the survey, women are asked whether they are allowed to go alone to the market, to a nearby

health facility, and outside the village. We create the mobility variable as a binary indicator that takes the value 1 if she is allowed to travel alone to at least one of these places and 0 otherwise. This variable captures whether a woman is permitted to freely move reflecting the degree of freedom granted to her within the household, rather than her actual movements. Results based on this mechanism are reported in Panel B of Table 5. Column (3) presents the effect of internet exposure on women's freedom of mobility, instrumented by adjusted tower density at district level. We find a 15 pp increase in her reported freedom of mobility as a result of internet exposure. As before, we use fitted values of mobility in our linear regression of IPV attitudes, bootstrapping the standard errors to account for the generated regressor. We find that increased freedom of mobility is significantly associated with a 22 pp reduction in her probability to justify IPV.

What we posit is that while internet exposure may not directly change a woman's physical movement, it can influence the underlying permission structures and norms at the household level about what is deemed as acceptable female behaviour and as such result in greater reported freedom of movement. First, by increasing women's access to information, communication methods, and digital literacy, internet exposure may enhance their perceived ability and value within the household, leading to a greater empowerment to move outside for acceptable purposes. Second, internet-connected women may gain exposure to new norms and role models that challenge traditional restrictions on women's autonomy, encouraging them to be more assertive including about the ability to leave the home. Third, from the household's perspective, the ability to stay in touch while outside the home through mobile phones may reduce safety concerns and social stigma.

7 Robustness

7.1 Disaggregated outcome measures

Our baseline outcome variables include questions that are asked to the women regarding their attitudes about whether beating the wife is justified in the following scenarios: (1) if the wife goes out without telling her husband, (2) neglects children, (3) argues with husband, (4) refuses sex, (5) does not cook food properly, (6) is unfaithful, and (7) is disrespectful. We code each response as taking the value 1 if their response is yes and 0 otherwise. For our baseline, we used an index of IPV attitudes that takes a value 1 if a woman justifies IPV for even any one scenario and 0 otherwise. Here, we estimate the effect of women's exposure to the internet on IPV attitudes for each of the seven scenarios separately.

Table 6 presents the results. The marginal effects across columns (1) through (7) are consistently negative and statistically significant effect at 1% level. In terms of magnitude, we find that a woman is 15 pp less likely to justify IPV in the event that she travels without informing anyone; 14 pp less likely if she neglects children, argues with husband or is disrespectful to her husband; 12 pp less likely if she is unfaithful; 11 pp less likely if she burns food and 8 pp less likely if she refuses to have sex. These results suggest that internet exposure leads to a reduction in acceptability of IPV across both traditionally serious justifications like infidelity or obligations or violation of marital expectations, and normative justifications related to more day-to-day behaviours, highlighting a shift in underlying gender norms.

7.2 Sensitivity analysis: trimmed instrument

We test the sensitivity of our baseline results by trimming our instrumental variable, adjusted tower density. Specifically, we first slice the top and bottom 1% of the IV, followed by 5% and then 10% respectively. We present the results in Table 7, columns (1), (2) and (3), respectively. Our results remain consistent with our baseline results. Column (1) shows a causal effect of 19 pp decline in the probability of a woman justifying IPV resulting from internet exposure. Column (2) 16 pp fall and column (3) a 17 pp fall in the probability of accepting patriarchal norms around IPV. Thus, our results do not seem to be driven by extreme values in the instrumental variable.

7.3 Sensitivity analysis: additional controls

Furthermore, we assess the robustness of our baseline results by introducing additional controls that capture more dimensions of household and contextual variation. Table 8 presents the results. First, we account for husband and parental characteristics which may be correlated with both a woman's exposure to the internet as well as her attitudes towards IPV. Husband's characteristics include his education, employment status, and frequency of alcohol consumption. Such factors have been shown in prior literature to correlate with women's bargaining power, IPV, and gender norms within households (Field et al., 2004; Krishnan et al., 2010; Shreemoyee et al., 2025). We also include an indicator for whether or not the woman witnessed her father physically abuse her mother as a proxy for intergenerational transmission of attitudes towards violence. As shown in column (1), even after the inclusion of these additional controls, the estimated effect of internet exposure on women's IPV attitudes remains a negative and statistically significant effect. The magnitude of impact is 20 pp and is both quantitatively and qualitatively similar to our baseline results, thus suggesting that our estimates are not confounded by these

omitted variables in the baseline.

Second, we test the robustness of our IV strategy to potential contamination from neighbouring districts' infrastructure, given the high prevalence of marriage migration among rural Indian women. It is common for women to relocate to nearby villages or districts after marriage, raising the concern that their reported internet exposure may reflect the infrastructure of a different district than the one used to construct our IV. If, for instance, a woman reports her internet use prior to migration, and tower density in her district of origin is correlated with the instrument in her district of interview, this could threaten the exclusion restriction. To address this, we include the average of the adjusted tower density of neighbouring districts as an additional control. From column (2), our results remain robust, showing that internet exposure leads to a 21 pp decline in the probability of justifying IPV. The effect continues to be statistically significant at the 1% level, reinforcing the credibility of our identification strategy.

Third, we include population density as an additional control in our analysis. Telecom companies may have prioritized more densely populated areas during network expansion, and attitudes towards IPV may also differ between high- and low-density areas due to greater opportunities for interaction among women in densely populated settings. To account for this, we calculate district-level population density using the 2011 Census and incorporate it as an additional control variable. Our results, reported in column (3), remain robust to the inclusion of this variable.

7.4 Alternative measures

We conduct additional robustness checks by altering the measurement of two key variables in our analysis, the proxy for local economic development as a control variable and the outcome variable. First, in our baseline specification, one of the district-level socioeconomic controls is nighttime lights intensity, which serves as a proxy for the level of local economic development. As an alternative measure, we replace nightlights with the district-level Multidimensional Poverty Index (MPI). The MPI, reported in the National Multidimensional Poverty Index Report (NITI Aayog, 2023), captures a broader conception of development and deprivation at the district level.

Second, we address a limitation of our baseline outcome variable, which aggregates women's attitudes towards IPV across seven scenarios recorded in the NFHS. While informative, this measure does not capture the intensity with which IPV is justified. To account for this, we construct an alternative outcome using an Inverse-Probability-Weighted (IPW) index of IPV attitudes. This approach weights the seven disaggregated components based on their prevalence in the sample, allowing us to construct a continuous intensity measure. We then create a binary

indicator from this index using the sample mean as the threshold. This binary variable captures whether a woman's justification of IPV lies above or below the average.

Table 9 presents the results. Column (1) shows that our results remain robust and consistent with the baseline when we replace nightlights with the MPI as the measure of district-level urbanization. The coefficient indicates that greater internet exposure leads to a 22 pp decline in women's justification of IPV. In column (2), where we use the IPW-based intensity measure of IPV attitudes as the outcome, we find a 19 pp decline. These estimates remain both qualitatively and quantitatively similar to our baseline results, reinforcing the robustness of our causal findings to alternative measurement strategies.

7.5 Falsification test

Further, we conduct two randomization inference tests to address concerns of spurious correlation and to strengthen confidence in our identification strategy. Our results, so far, have consistently shown a negative and statistically significant effect of women's internet exposure on their attitudes justifying IPV. The first test evaluates whether such an effect could arise purely by chance through random assignment of the outcome variable. Specifically, we retain the actual first-stage relationship between the instrument (district-level log transformation of tower density) and the endogenous regressor (women's internet exposure), but randomly reassign the outcome variable. That is, we associate a woman i's instrumented internet exposure with a randomly selected woman j's IPV attitudes. This breaks the structural relationship between internet exposure and IPV attitudes while preserving the strength of the first stage.

In the second test, we randomize the instrumental variable itself by shuffling the district-level tower density across districts. This disrupts the first-stage relationship by breaking the link between a woman's internet exposure and the actual tower density in her district. Both tests serve as falsification tests. The first isolates the variation in our outcome variable and the second challenges the validity of our IV.

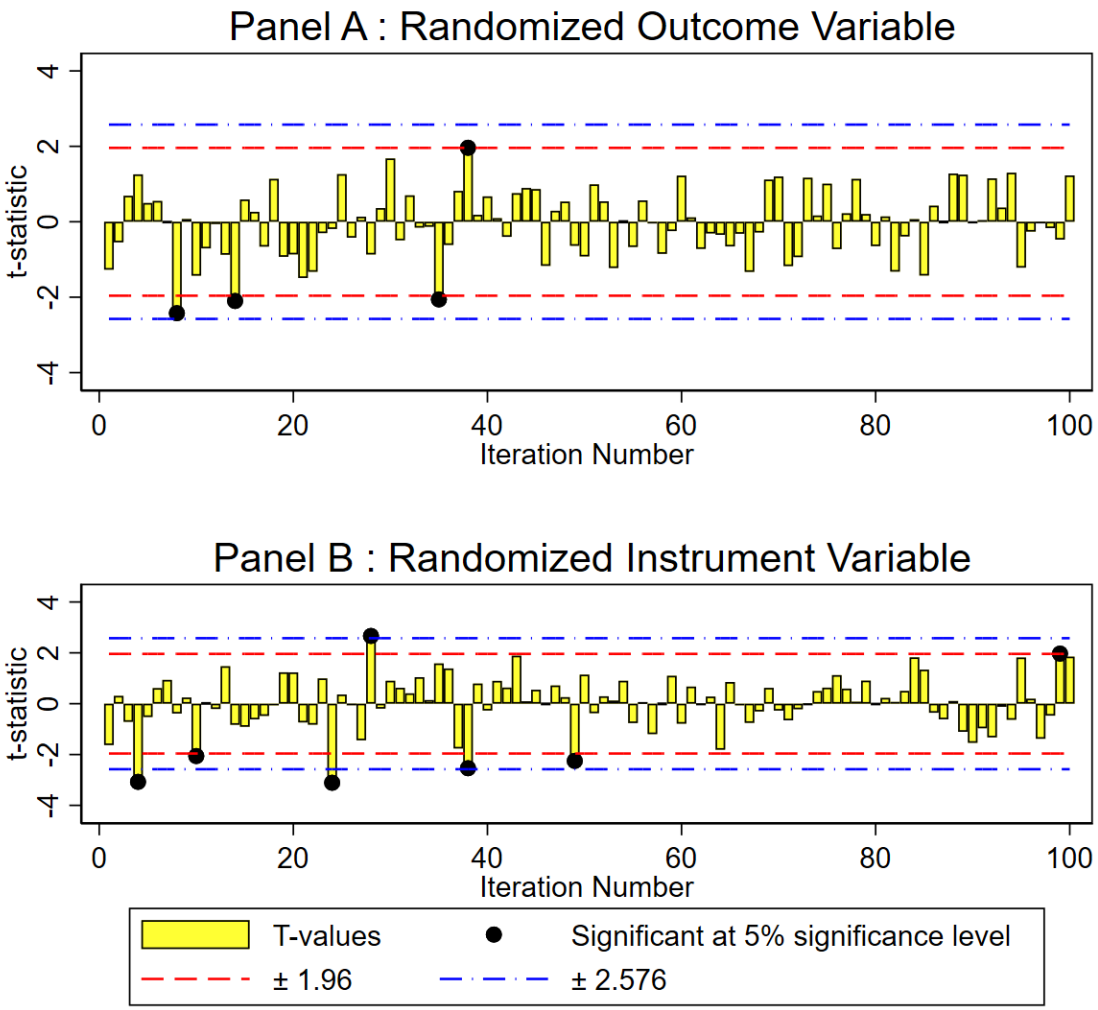

Figure 5: Falsification analysis

We replicate each 100 times and present the distribution of t-statistics in Fig 5. From 5A, we find that 4 out of 100 times, we are unable to reject the null the effect of internet exposure is equal to zero. This implies that 96% of the time, the effect of internet exposure on IPV attitudes is not statistically significant when the outcome is randomized. Fig 5B shows that 93% of the time we do not find a statistically significant association between adjusted tower density ansd internet exposure when the IV is randomized. These results strongly suggest that our main estimates are not driven by random chance and support the validity of our causal identification strategy.

8 Sub-sample analysis

Next, we examine whether the effect of women's internet exposure on their attitudes towards IPV varies across interesting sub-populations. To do so, we conduct sub-sample analyses based on individual and household-level characteristics, including women's *education, social group, wealth index, and area of residence*. For each sub-sample, we re-estimate the effect of internet exposure on IPV attitudes, controlling for the full set of women-, household-, geographic-, and socioeconomic characteristics, as well as state fixed effects.

In addition, we examine heterogeneity by regional classifications of states. Specifically, we disaggregate the sample by *North, Central, East, West, South, North-East, Empowered Action Group (EAG) states, and a category that excludes the North-Eastern states and Union Territories*. Panels A and B of Table 10 present the results of these sub-sample analyses using our most preferred specification.

8.1 By women level and household characteristics

By women's education: Column (1) of Panel A presents the results for the sub-sample of women with less than the mean level of education i.e. 7.39 years, and column (2) for women with education equals to or above the mean. Again, we note that the effect of internet exposure on women's probability of accepting wife-beating norms is negative and statistically significant, regardless of education levels. The effect is 26 pp for women with less education and 14 pp for more educated women, although we cannot conclude that the effects are statistically different.

By social group: Social group continues to play an important role in influencing women's autonomy, mobility and access to resources (Deshpande, 2011; Thorat and Newman, 2007). We divide the sample into two groups, specifically, backward and non-backward sub-samples. Columns (3) and (4) present the results. We find that women's internet exposure leads to a statistically significant decline in the likelihood of women justifying norms that accept IPV across both sub-samples. The magnitude of impacts show a 20 pp reduction for the women belonging to backward social group and 23 pp fall for the non-backward social group.

By wealth index: Household wealth can influence not only material access to the internet but could also affect women's ability to translate digital access to attitudinal changes (Jayachandran, 2015). As such, we study the heterogeneous effects of internet exposure on IPV attitudes across wealth categories in columns (5) and (6). We slice the sample to poor and non-poor households based on the NFHS-5 wealth index categories. We define a household as *Poor* if the wealth index of that household is either poor or poorest in the DHS wealth index. Households whose wealth index is higher than poor category are categorized as *Non-Poor*. Our results show that there

is a statistically significant and negative effect of internet exposure on women's IPV attitudes across both poor and non-poor households. The magnitude of impact is 20 pp for non-poor and 13 pp for the poor households, respectively. The larger effect among non-poorer households suggests that internet exposure may be particularly empowering where the baseline levels of awareness are higher.

By area of residence: Rural and urban contexts often differ in terms of infrastructure, gender norms, and digital literacy. Hence, in columns (7) and (8), we examine the heterogeneity across rural and urban residences. As before, we find that across both sub-samples, the effect of internet exposure on the probability of justifying attitudes about IPV is negative and statistically significant. Women in rural areas are 18 pp less likely to justify norms around IPV due to internet exposure, whereas women in the urban households are 22 pp less likely to accept wife beating norms as a result of digital exposure. While the magnitude is higher in urban areas, we are unable to explain whether or not this difference is statistically significant.

8.2 By classification of states

India's regions vary substantially in terms of gender norms and cultures (Jejeebhoy and Sathar, 2001). As such, we study the heterogeneity in the effect of internet exposure on women's attitudes justifying IPV by different regions of India. Panel B of Table 10 presents the results. Column (1) to (6) represent the estimates for the North, Central, East, West, South, North-East of India, respectively. Barring the sub-sample of only North Eastern states, we see the consistently negative and robust effect of internet exposure on women's probability of accepting attitudes that justify IPV, and the magnitude of impact ranges from 9 pp to 28 pp. Perhaps, the null effect of internet exposure for North-Eastern states reflects a more gender-equitable baseline norms.

Column (7) shows the effect of internet exposure on IPV attitudes for the EAG states of Bihar, Jharkhand, Odisha, Chhattisgarh, Madhya Pradesh, Uttar Pradesh, Uttarakhand, and Rajasthan. For this sub-sample, we find that internet exposure leads to a 21 pp decline in the likelihood of accepting IPV attitudes. Column (8) presents the results when the sample is restricted to all the states excluding North-Eastern states and the union territories of India. We find a similar effect of a 21 pp decline in the likelihood of acceptance of IPV attitudes with internet exposure for this sub-sample as well.

9 Conclusion, Discussion and Limitations

We provide new causal evidence on the relationship between women's internet exposure and their attitudes toward intimate partner violence (IPV), using nationally representative data from NFHS-5. Utilizing an instrumental variables strategy that exploits exogenous variation in district-level mobile tower density, across a range of specifications, we find that internet exposure significantly reduces the likelihood that women justify IPV. This result is robust to the inclusion of a comprehensive set of individual, household, and district-level controls, alternative measures of both urbanization and the IPV attitude outcome, and falsification tests based on randomization inference.

We also explore heterogeneity in this effect across social and economic margins. The impact of internet exposure on IPV attitudes is consistently negative and statistically significant across margins defined by caste, wealth, residence, and women's education levels. The effect is particularly pronounced among women from non-poor households, and those residing in urban areas, perhaps suggesting digital exposure can shift regressive attitudes towards IPV when women are empowered with enabling resources. On similar lines, regional heterogeneity further underscores the role of context. We find robust effects in most parts of the country, including the EAG states, where patriarchal gender norms are more deeply entrenched. However, the effect is not statistically significant in the North-East, a region known for more egalitarian gender norms and some matrilineal systems. We posit that the null effect for North Eastern states may reflect a ceiling effect, where IPV-justifying attitudes are already low and thus limiting the scope for further change through internet exposure (Nambiar et al., 2025).

Taken together, these findings suggest that digital exposure is a potentially transformative tool in reshaping patriarchal gender norms. We also provide evidence that internet exposure may alter attitudes by improving women's awareness that could expose them to alternative narratives, reduce isolation, or provide platforms for peer interaction and solidarity. Women's awareness increases by 24 pp as a result of internet exposure, which in turn reduces women's probability of justifying IPV. Additionally, increased internet exposure also increases women's perceived mobility by 15 pp, suggesting greater confidence to navigate physical spaces beyond the home. That said, the findings of this paper should be interpreted in light of the following limitations. First, our treatment variable captures women's ever exposure to the internet, without distinguishing variation in the intensity or frequency of use. While our identification strategy enables us to estimate the average effect of internet exposure, it remains possible that the magnitude of the effect is greater among women with more intensive or sustained engagement online. Second, the data do not allow us to observe the nature or quality of the content accessed

by women. As a result, we cannot speak to whether specific types of online content mediate or condition the relationships documented in this study.

From a policy perspective, the results highlight the need to view digital inclusion not only as an infrastructure or connectivity priority for policymakers but also as a crucial tool for advancing gender justice and reshaping attitudes toward violence against women. We show that in contexts where such norms are deeply internalized and often seen as part of everyday life, digital connectivity can provide a new perspective, expand access to information and enhance both physical and social mobility. Digital inclusion in such societies can have far-reaching consequences, not only for women's participation in the digital economy, but also for improving their autonomy, safety, and dignity in everyday life.

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Table 1: Descriptive Statistics: Woman- and household-level variables

Variable	Mean	SD	Min	Max
Outcome Variable				
Attitudes towards IPV: Justifies IPV				
Yes	0.43	0.49	0.00	1.00
No	0.57	0.49	0.00	1.00
Treatment Variable				
Internet use				
Yes	0.33	0.47	0.00	1.00
No	0.67	0.47	0.00	1.00
Women's Characteristics				
Age (in years)	30.62	9.89	15.00	49.00
Years of education	7.39	5.16	0.00	20.00
Employment status (last 12 months)				
Employed	0.32	0.47	0.00	1.00
Not employed	0.68	0.47	0.00	1.00
Duration of residence (in years)	15.88	9.83	0.00	49.00
Currently married				
Yes	0.71	0.45	0.00	1.00
No	0.25	0.43	0.00	1.00
Never in union	0.04	0.20	0.00	1.00
Media exposure				
Yes	0.76	0.43	0.00	1.00
No	0.24	0.43	0.00	1.00
Land/House ownership				
Yes	0.47	0.48	0.00	1.00
No	0.53	0.48	0.00	1.00
Household Characteristics				
Male-headed household				
Yes	0.84	0.37	0.00	1.00
No	0.16	0.37	0.00	1.00
Age of HH head (in years)	48.22	12.85	14.00	95.00
Number of HH members	5.33	2.33	1.00	26.00
Religion				
Hindu	0.75	0.43	0.00	1.00
Muslim	0.13	0.33	0.00	1.00
Other	0.12	0.33	0.00	1.00
Social Group				
Scheduled Caste	0.19	0.39	0.00	1.00
Scheduled Tribe	0.19	0.39	0.00	1.00
OBC	0.39	0.49	0.00	1.00
Other/None	0.18	0.39	0.00	1.00
Don't know/Missing	0.05	0.22	0.00	1.00
Wealth category				
Poor	0.43	0.50	0.00	1.00
Non-poor	0.57	0.50	0.00	1.00
Residence				
Rural	0.75	0.43	0.00	1.00
Urban	0.25	0.43	0.00	1.00
Observations		102,203		

Notes: Women who are widowed, divorced, separated, or not living with their husband are coded as currently unmarried. Women who have never married or whose gauna has not been performed are classified as 'never in union'. Media exposure indicates exposure to newspapers, radio, or television. House/land ownership includes sole or joint ownership. Other religions include Christian, Sikh, Buddhist/Neo-Buddhist, Jain, Jewish, Parsi/Zoroastrian, no religion, and others. The bottom two DHS wealth quintiles are coded as poor; all others as non-poor.

Table 2: Descriptive Statistics: District-level variables

Variable	Mean	SD	Min	Max
Socioeconomic Characteristics				
Primary schools	1628.62	1125.47	17.00	7097.00
Middle schools	742.75	549.05	0.00	4133.00
Secondary schools	326.79	301.85	1.00	2762.00
Medical colleges	2.29	4.75	0.00	51.00
Engineering colleges	6.36	12.74	0.00	148.00
Arts and science colleges	14.75	17.17	0.00	113.00
Vocational training institutes	14.23	24.10	0.00	269.00
Family welfare centres	107.13	1058.19	0.00	7196.00
Maternity and child welfare centres	63.87	105.03	0.00	1799.00
Sex ratio (female/male)	947.16	60.29	533.57	1184.40
SC and ST population share (in percentage)	33.09	22.74	0.34	98.58
Geographical Characteristics				
Elevation	5.49	1.21	1.41	8.53
Ruggedness	1.94	0.76	0.96	4.05
Nightlights	0.60	0.53	0.00	3.88
Number of lightning days	2.10	1.34	0.00	6.23
Vegetation Continuous Fields	16.89	15.21	0.00	72.89
Instrument Variable				
Number of towers	3123.51	7703.83	0.00	126593.00
Tower density	3.07	18.93	0.00	249.69
Adjusted tower density	0.49	0.77	0.00	5.52
Observations		692		

Notes: To minimize the influence of extreme values, the following variables ruggedness nightights, elevation, and number of lightning days, are expressed in their natural logarithmic form after adding one to them. Similarly, adjusted tower density is computed as log(1+tower density). Tower density represents the number of towers within a district divided by its land area (measured in squares km).

Table 3: First stage analysis: Estimates of the relationship between adjusted tower density and women's internet exposure.

	Internet Exposure			
	(1)	(2)	(3)	(4)
Adjusted Tower Density	0.11***	0.03***	0.05***	0.07***
	(0.01)	(0.00)	(0.01)	(0.01)
Observations	1,02,203	1,02,203	1,02,203	1,02,203
Women's characteristics	No	Yes	Yes	Yes
Household characteristics	No	Yes	Yes	Yes
Geographical characteristics	No	No	Yes	Yes
Socioeconomic Characteristics	No	No	Yes	Yes
State fixed effects	No	No	No	Yes
Kleibergen–Paap rk LM statistic	197.15	46.63	35.73	54.01
Cragg–Donald Wald F statistic	5124.38	469.71	151.97	212.03
Kleibergen–Paap Wald rk F statistic	329.28	49.35	36.48	54.32
R-squared	0.05	0.34	0.34	0.35

Notes: Estimation via OLS regression analysis. Column (1) has no additional controls. Column (2) includes women- and household-level characteristics. Column (3) additionally adjusts for geographical and socioeconomic characteristics, while Column (4) further includes state fixed effects. Women's characteristics include age, current marital status, years of completed education, duration of residence at the current location, employment status (last 12 months), media exposure, and land/house ownership. Household characteristics include indicators for the sex of the household head, age of the household head, household size, religion, social group, wealth status, and area of residence. District-level socioeconomic characteristics include the sex ratio, percentage SC and ST population, number of primary schools, middle schools, secondary schools, medical colleges, engineering colleges, arts and science colleges, vocational colleges, family welfare centres, maternity and child welfare centres. Geographical controls include district-level ruggedness, nightlights, elevation, annual number of days with lightning, and vegetation continuous fields. Standard errors (in parentheses) are clustered at the neighbourhood level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 4: Probit and IV analysis: Estimates of the effect of women's internet exposure on their attitudes towards IPV.

	Women's Attitudes towards IPV							
	Panel A: Probit				Panel B : IV			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Internet Exposure	-0.11***	-0.07***	-0.07***	-0.05***	-0.07	-0.12***	-0.16***	-0.21***
	(0.01)	(0.01)	(0.01)	(0.01)	(0.06)	(0.03)	(0.03)	(0.02)
Observations	1,02,203	1,02,203	1,02,203	1,02,203	1,02,203	1,02,203	1,02,203	1,02,203
Women's characteristics	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Household characteristics	No	Yes	Yes	Yes	No	Yes	Yes	Yes
Geographical characteristics	No	No	Yes	Yes	No	No	Yes	Yes
Socioeconomic characteristics	No	No	Yes	Yes	No	No	Yes	Yes
State fixed effects	No	No	No	Yes	No	No	No	Yes

Notes: Columns (1) - (4) presents the findings from the Probit estimation, whereas columns (5) - (8) reports the results from the Conditional Mixed Process (CMP) estimation. Columns (1) and (5) has no additional controls. Columns (2) and (6) include women- and household-level characteristics. Columns (3) and (7) additionally adjust for geographical and socioeconomic characteristics, while columns (4) and (8) further include state fixed effects. Women's characteristics include age, current marital status, years of completed education, duration of residence at the current location, employment status (last 12 months), media exposure, and land/house ownership. Household characteristics include indicators for the sex of the household head, age of the household head, household size, religion, social group, wealth status, and area of residence. District-level socioeconomic characteristics include the sex ratio, percentage SC and ST population, number of primary schools, middle schools, secondary schools, medical colleges, engineering colleges, arts and science colleges, vocational colleges, family welfare centres, maternity and child welfare centres. Geographical controls include district-level ruggedness, nightlights, elevation, annual number of days with lightning, and vegetation continuous fields. Standard errors (in parentheses) are clustered at the cluster level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 5: Mechanism: Estimates of the effect of women's internet exposure on their awareness and mobility.

	Panel A		Panel B	
	IV	OLS	IV	OLS
	Awareness	Attitudes towards IPV	Mobility	Attitudes towards IPV
	(1)	(2)	(3)	(4)
Internet Exposure	0.24***		0.15***	
	(0.02)		(0.02)	
Fitted Awareness		-0.13***		
		(0.01)		
Fitted Mobility				-0.22***
				(0.03)
Observations	91,213	91,213	1,02,203	1,02,203
Women's Characteristics	Yes	Yes	Yes	Yes
Household Characteristics	Yes	Yes	Yes	Yes
Geographical Characteristics	Yes	Yes	Yes	Yes
Socioeconomic Characteristics	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes

Notes: Columns (1) and (3) report estimates from CMP, whereas columns (2) and (4) present results from OLS regression. Both the panels include include women- and household-level characteristics, geographical characteristics, socioeconomic characteristics, and state fixed effects. Women's characteristics include age, current marital status, years of completed education, duration of residence at the current location, employment status (last 12 months), media exposure, and land/house ownership. Household characteristics include indicators for the sex of the household head, age of the household head, household size, religion, social group, wealth status, and area of residence. District-level socioeconomic characteristics include the sex ratio, percentage SC and ST population, number of primary schools, middle schools, secondary schools, medical colleges, engineering colleges, arts and science colleges, vocational colleges, family welfare centres, maternity and child welfare centres. Geographical controls include district-level ruggedness, nightlights, elevation, annual number of days with lightning, and vegetation continuous fields. Standard errors (in parentheses) are clustered at the cluster level in columns (1) and (3). Standard errors are bootstrapped with 100 replications to avoid the generated regressor problem in columns (2) and (4). ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 6: Disaggregated outcome variable: Estimates of the effect of women's internet exposure on justification of IPV for various scenarios.

	Woman's Justification of IPV for various reasons						
	Travels without informing	Neglects Children	Argues with husband	Refuses to have sex	Burns the food	Unfaithful	Disrespectful
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Internet Exposure	-0.15***	-0.14***	-0.14***	-0.08***	-0.11***	-0.12***	-0.14***
	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)	(0.02)
Observations	1,01,971	1,02,050	1,01,938	1,01,593	1,02,029	1,01,893	1,02,010
Women's Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographical Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomic Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimation based on CMP analysis. The outcome variables are woman's attitudes towards IPV for various reasons. Women's characteristics include age, current marital status, years of completed education, duration of residence at the current location, employment status (last 12 months), media exposure, and land/house ownership. Household characteristics include indicators for the sex of the household head, age of the household head, household size, religion, social group, wealth status, and area of residence. District-level socioeconomic characteristics include the sex ratio, percentage SC and ST population, number of primary schools, middle schools, secondary schools, medical colleges, engineering colleges, arts and science colleges, vocational colleges, family welfare centres, maternity and child welfare centres. Geographical controls include district-level ruggedness, nightlights, elevation, annual number of days with lightning, and vegetation continuous fields. Standard errors (in parentheses) are clustered at the cluster level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 7: Robustness analysis by trimming the extreme values of the instrument variable.

	Woman's Attitudes towards IPV		
	(1)	(2)	(3)
Internet Exposure	-0.19***	-0.16***	-0.17***
	(0.02)	(0.02)	(0.02)
Observations	99,858	91,821	81,521
Women's Characteristics	Yes	Yes	Yes
Household Characteristics	Yes	Yes	Yes
Geographical Characteristics	Yes	Yes	Yes
Socioeconomic Characteristics	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes

Notes: Estimation via CMP estimation. Columns (1), (2), and (3) excludes the top as well as bottom 1%, 5%, and 10% of the adjusted tower density, respectively. All specifications include women's characteristics, household characteristics, district-level socioeconomic and geographic controls, and state fixed effects. Standard errors (in parentheses) are clustered at the cluster level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 8: Robustness analysis by including additional controls.

	Woman's Own Attitudes towards IPV		
	(1)	(2)	(3)
Internet Exposure	-0.20***	-0.21***	-0.20***
	(0.03)	(0.02)	(0.02)
Observations	57,445	1,02,203	1,02,203
Women's Characteristics	Yes	Yes	Yes
Household Characteristics	Yes	Yes	Yes
Geographical characteristics	Yes	Yes	Yes
Socioeconomic Characteristics	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes
Husband & Parental Characteristics	Yes	No	No
Neighbouring Districts' Tower Density	No	Yes	No
Population Density	No	No	Yes

Notes: Estimation via Conditional Mixed Process (CMP) estimation. All specifications include women's characteristics, household characteristics, district-level socioeconomic and geographic controls, and state fixed effects. Additionally, column (1) includes husband and parental characteristics: husband's education, employment in the last 12 months, age, and frequency of drinking as well has woman's exposure to interparental violence (=1 if yes and 0 otherwise). Column (2) includes the average tower density of all the neighbouring districts as an additional control. In column (3), we have added UN predicted population density for the year 2020 as a control. Standard errors (in parentheses) are clustered at the cluster level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 9: Robustness analysis based on alternative construction of outcome variable and control.

	Woman's Own Attitudes towards IPV	
	(1)	(2)
Internet Exposure	-0.22***	-0.19***
	(0.02)	(0.02)
Observations	1,02,203	1,00,957
Women's Characteristics	Yes	Yes
Household Characteristics	Yes	Yes
Geographical characteristics	Yes	Yes
Socioeconomic Characteristics	Yes	Yes
State Fixed Effects	Yes	Yes

Notes: Estimation via CMP estimation. All specifications include women's characteristics, household characteristics, district-level socioeconomic and geographic controls, and state fixed effects. Additionally, in column (1), we use the district-level multidimensional poverty index as an alternative control for urbanisation instead of nightlights. In column (2), we construct an Inverse Probability Weighted Index of the outcome variable by applying the inverse probability approach to its disaggregated components. This index is then converted into a binary measure using the sample mean as the cut-off. Standard errors (in parentheses) are clustered at the cluster level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Table 10: Heterogeneity analysis based on women's characteristics, household characteristics, and regions.

	Panel A: Women's and Household Characteristics							
	Education		Social Group		Wealth		Residence	
	Low	High	Backward	Others	Poor	Non-Poor	Rural	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Internet Exposure	-0.26***	-0.14**	-0.20***	-0.23***	-0.13**	-0.20***	-0.18***	-0.22***
	(0.07)	(0.07)	(0.02)	(0.04)	(0.05)	(0.03)	(0.03)	(0.04)
Observations	43,353	58,850	78,265	18,609	43,892	58,305	77,048	25,155
	Panel B: Regions							
	North	Central	East	West	South	North-East	Empowered Action Group (EAG)	All States except North-East & UTs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Internet Exposure	-0.09**	-0.14***	-0.21***	-0.28***	-0.12***	-0.04	-0.21***	-0.21***
	(0.04)	(0.05)	(0.05)	(0.06)	(0.04)	(0.07)	(0.03)	(0.02)
Observations	20,378	23,706	17,004	10,078	15,752	14,940	45,814	80,961
Women's Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Geographical Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Socioeconomic Characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Estimation via CMP estimation. Panel A reports subsample estimates by women's and household characteristics. Columns (1)–(2) present results for women with below-average (¡7.39 years) and above-average (7.39 years) education, respectively. Column (3) includes households belonging to SC, ST, or OBC, while Column (4) covers other social groups. Columns (5) and (6) report estimates for poor and non-poor households, respectively. Columns (7) and (8) present results for rural and urban residents, respectively. Panel B reports subsample analyses by regional classifications. Column (1) corresponds to Northern states and Union Territories (UTs): Jammu and Kashmir, Himachal Pradesh, Punjab, Chandigarh, Uttarakhand, Haryana, Delhi, and Rajasthan. Column (2) includes the Central region (Uttar Pradesh, Chhattisgarh, Madhya Pradesh), Column (3) covers the Eastern region (Bihar, West Bengal, Jharkhand, Odisha), Column (4) the Western region (Gujarat, Dadra and Nagar Haveli and Daman and Diu, Maharashtra, Goa), Column (5) the Southern region (Andhra Pradesh, Telangana, Karnataka, Lakshadweep, Kerala, Tamil Nadu, Puducherry, Andaman & Nicobar Islands), Column (6) the Northeastern region (Sikkim, Arunachal Pradesh, Nagaland, Manipur, Mizoram, Tripura, Meghalaya, Assam), Column (7) the Empowered Action Group (EAG) states (Bihar, Jharkhand, Odisha, Chhattisgarh, Madhya Pradesh, Uttar Pradesh, Uttarakhand, Rajasthan), and Column (8) excludes Northeastern states and UTs from the overall sample. All specifications include women's characteristics, household characteristics, district-level socioeconomic and geographic controls, and state fixed effects. Standard errors (in parentheses) are clustered at the cluster level. ***, **, and * represent significance at 1%, 5%, and 10%, respectively.

Appendix

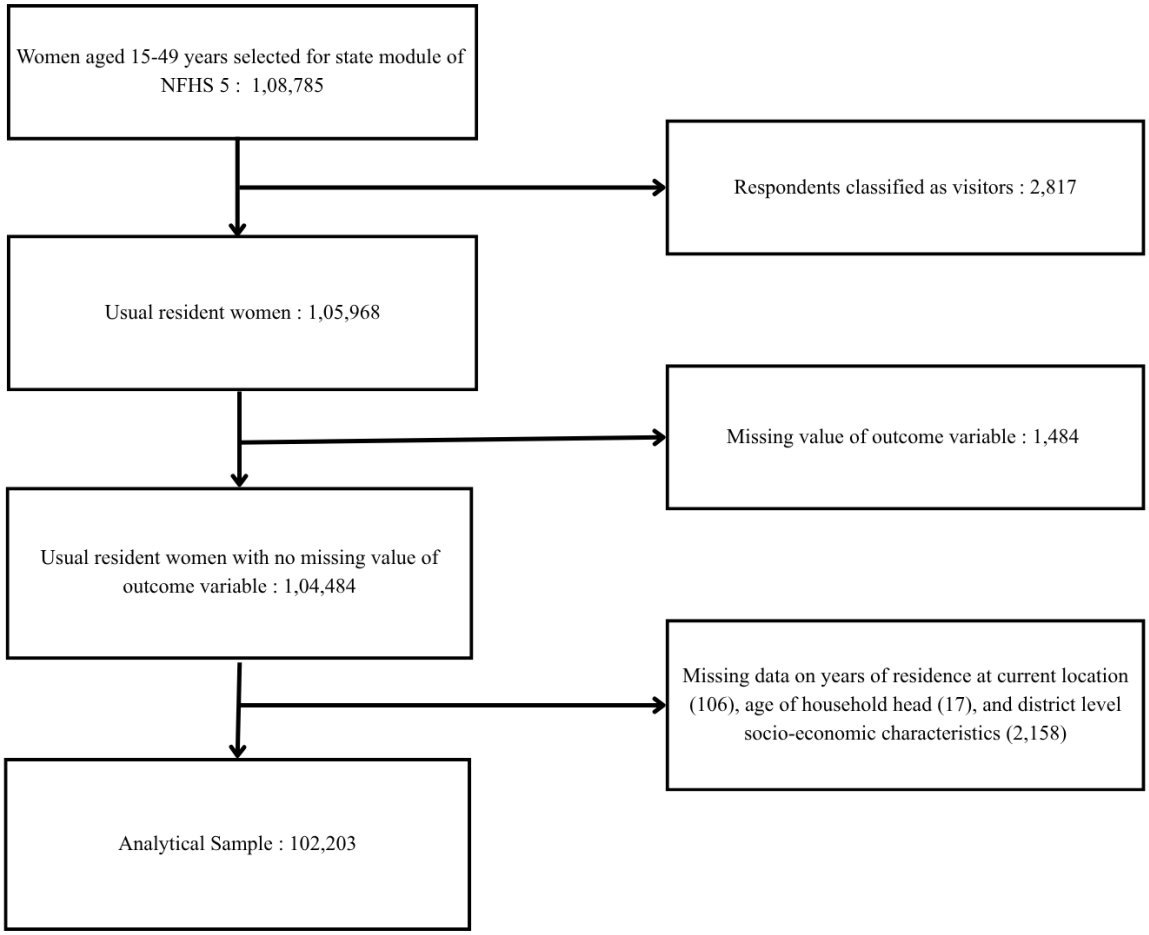

Figure A1: Analytical Sample formation