Fall 9-4-2024

Hold the Phone: The Short- and Long-Run Impacts of Connecting Indian Women to Digital Technology

Giorgia Barboni
Warwick University, giorgia.barboni@wbs.ac.uk

Anwesha Bhattacharya
Harvard University, anweshabhattacharya@fas.harvard.edu

Erica Field
Duke University, field.erica@duke.edu

Rohini Pande
Yale University, ROHINI.PANDE@YALE.EDU

Natalia Rigol
Harvard University, nrigol@hbs.edu

See next page for additional authors

Authors

Giorgia Barboni, Anwesha Bhattacharya, Erica Field, Rohini Pande, Natalia Rigol, Simone Schaner, Aruj Shukla, and Charity Moore

Hold the Phone: The Short- and Long-Run Impacts of Connecting Indian Women to Digital Technology*

Giorgia Barboni
Warwick University

Anwesha Bhattacharya
Harvard University

Erica Field
Duke University

Rohini Pande
Yale University

Natalia Rigol
Harvard Business School

Simone Schaner
Univ. of Southern California

Aruj Shukla
Univ. of Southern California

Charity Troyer Moore
Yale University

September 4, 2024

Abstract

Access to smartphones and mobile internet is increasingly necessary to participate in the modern economy. Yet women significantly lag men in digital access, especially in lower-income settings with gender gaps that span other dimensions - and where digital gaps threaten to deepen existing analog inequities. We study the short- and long-term effects of a large-scale state-sponsored program in India that aimed to close digital

*We are grateful for expert research assistance and management from Thomas van den Aarssen, Hemawathy Balarama, Shreya Chandra, Vidushi Dhawan, Akshat Goel, Aashima Goyal, Prakash Gupta, Ranae Jabri, Harsh Jaiswal, Erik Jorgensen, Nikita Kohli, Ankesh Kumar, Shreya Mathur, Urvi Naik, Savannah Noray, Fatema Patel, Shehanas Pahzoor, Rashi Sabherwal, Sonya Seuter, Abhishek Sharma, Jillian Stallman, Natalie Theys, Tejita Tiwari, Tanya Vaidya, Balasai Vanukuri, and Rosemary Zhang. We also thank the exceptional data collection teams at Inclusion Economics India Centre and ID Insight. This research was supported by funds from Pivotal Ventures, the Social Science Research Council's Mercury Project, USAID Development Innovations Ventures, the National Science Foundation Grant Number 1949522, the Gender, Growth, and Labour Markets in Low Income Countries Programme, the Initiative for What Works to Advance Women and Girls in the Economy, and the Women's Economic Empowerment and Digital Finance Initiative. Data collection protocols were approved by IRBs at Harvard University (IRB17-0987), Yale University (2000025938, 2000032964) and the Institute for Financial Management and Research India. The study, including a pre-analysis plan, is registered in the 3IE Registry for International Development Impact Evaluations (study ID RIDIE-STUDY-ID-64be2e93463dc).
Emails: Barboni (Giorgia.Barboni@wbs.ac.uk), Bhattacharya (anweshabhattacharya@fas.harvard.edu), Field (field.erica@duke.edu), Pande (rohini.pande@yale.edu), Rigol (nrigol@hbs.edu), Schaner (schaner@usc.edu), Shukla (arujshuk@usc.edu), Troyer Moore (charity.moore@yale.edu).

gender gaps by transferring free smartphones to women while constructing 4G towers to bring rural areas online. The program was well implemented, reversing gender gaps in smartphone ownership in the short run. However, many women lost ownership and gender gaps in use quickly worsened as men made use of the new phones. Nearly 5 years after the program began, we find limited evidence of persistent effects across a range of outcomes, including phone ownership and use, gender norms, access to information, and local economic activity, although we do find some evidence of sectoral reallocation in the labor market. Despite widespread increase in smartphone adoption across households, digital gender gaps persist and were not affected by the program. Our findings suggest that in gender-unequal, resource-constrained settings, addressing affordability alone may not close digital gender gaps.

1 Introduction[1]

Mobile phones are rapidly reshaping the world's economies and societies. We know, for example, that even basic 2G mobile connectivity improves market functionality (Aker and Fafchamps, 2015; Jensen, 2007), helps people learn about job opportunities (Dammert et al., 2015), affects political coordination and mobilization (Manacorda and Tesei, 2020), and can support access to information relevant to education and health (Dammert et al., 2014; Aker et al., 2012), as well as poverty-reducing financial services (Suri and Jack, 2016). The evidence on the second generation of digital technology, which brought internet-enabled mobile phones, is more limited, but it appears that this advancement has been similarly important for both economic and non-economic outcomes, particularly in lower-income settings.[2]

Smartphones and mobile Internet lower information access costs and make it easier for users to engage with essential services, like banking and health consultations, without traveling to a service provider. Even digital work is becoming accessible to lower-income populations (Ho et al., 2024; Jalota and Ho, 2024). Such innovations could be particularly beneficial for women, who are often more constrained than men in mobility, agency, economic engagement, and human capital (Jayachandran, 2021). Digital technology may connect women to information, jobs, and more, even while addressing several of these dimensions of gender inequality. Yet in many lower-income countries,internet-enabled mobile phone access is unequal, reflecting broader economic and social disparities. For example, a recent survey found that women across 12 lower-income countries were 20 percentage points less likely than men to have recently used mobile internet (GSMA, 2022). Without equal access to mobile internet and phones, women may miss out on their benefits. Furthermore, if conservative norms depress women's access or return to digital technology, a marginalization trap may emerge, in which norms continue to limit women's technology adoption, potentially *widening* other gender gaps. As a result, understanding how access to new digital technology impacts gender

[1]This white paper incorporates and adapts text from other intermediate outputs, namely our pre-analysis plan (Barboni et al., 2023) and a technical report summarizing short-run effects of the phone distribution (Barboni et al., 2019).

[2]For example, Guriev et al. (2019) find mobile Internet reduces trust in government as citizens learn more about corruption through social media. Economic impacts of Internet-enabled phones include gender-differentiated labor market changes (Chiplunkar and Goldberg, 2022a), discussed later in this paper, and influence plans to migrate for work (Adema et al., 2022).

gaps, as well as identifying tools to ensure women fully benefit from these technologies is a research and policy priority.

Digital gender gaps in South Asia are particularly concerning (Banu, 2016). In India, our study location, only 59% of rural Indian women own a mobile phone, compared to 80% of males, and are less than half as likely to use mobile Internet or own a smartphone (Pew Research Center, 2019; GSMA, 2019). India's digital gender gap likely reflects a combination of economic and norms-related factors. In line with conservative gender norms, Indian women are less economically active than males and may therefore lack resources to purchase phones and data, and have lower actual and perceived economic returns to using phones. Women also lag men in digital and practical literacy, further depressing their relative returns. Alongside economic constraints, there is cultural opposition to women using phones, reflecting concerns that digital technologies may threaten unmarried women's "purity" and distract married women from caretaking responsibilities (Barboni et al., 2018).

This paper studies the short- and long-term impacts of an ambitious at-scale program designed to connect rural Indian villages to mobile internet and give women free smartphones and data. Under the Sanchar Kranti Yojana (SKY) program, the state government of Chhattisgarh distributed over 2 million smartphones to rural women in 2018. The government ensured all program villages had LTE (4G) coverage, and all phones received 1 GB of free data each month for six months to bring women and their families online. The program was gender-targeted, with women receiving the phones. SKY was implemented across approximately one-third of villages statewide. Eligibility in rural areas (our focus) was community-based, targeting villages with a population of 1,000 or more. Approximately 8,000 mobile towers were constructed to ensure all eligible locations had 4G network coverage. Smartphones were distributed to one adult female per household in village clusters (called gram panchayats, or GPs) with a population of at least 1,000 in their largest village. GPs just under this population threshold were ineligible.

We use an event study design to study the short-term impact of SKY, drawing on survey data collected in the capital district a few weeks before and after phone distribution. To investigate long-term effects, we use a regression discontinuity approach, utilizing primary statewide survey data collected nearly five years after the program concluded. Both surveys enrolled men and women from a common set of households, allowing us to examine impacts on women *and* on gender gaps, which is critical for understanding the distributional effects of the program. Our short and long-term analyses aim to identify the causal impact of SKY on women's access to and ownership of smartphones, gender gaps in phone use, and phone-related gender norms.

In addition to studying whether SKY closed digital gender gaps, we study broader downstream effects of the program, which (in the short term) led to an immediate, dramatic shift in access to smartphones and mobile Internet in rural areas. Improved availability of mobile phones and internet could have far-reaching effects in terms of local economic activity, labor markets, and access to information and financial services. Impacts may be gender-specific, consistent with recent research highlighting the nuanced implications of 3G rollout on male and female economic activity.[3] Our study period also covers the Covid-19 pandemic, providing a window to understand whether access to mobile technology affected access to, and interpretation of, information, and how impacts differed by gender.

In the short-term, SKY reversed the gender gap in smartphone ownership and views on the appropriateness of women's phone usage liberalize among both genders. Yet, the program failed to fully achieve its goal of closing digital gender gaps. Specifically, while smartphone use increased for both genders, men reported larger gains, such that gender gaps in usage actually worsened. Some of this worsening likely reflected women's inability to retain control over the new phone: Within a month of receiving smartphones, and despite 98% of eligible women reporting SKY phone receipt, approximately 40 percent of women no longer claimed they owned a smartphone. In contrast, men's reported smartphone ownership increased by 17 percentage points. Parallel to this, immediately after SKY phone distribution, male respondents were more likely to report that men have more use for phones than women. To the extent that households do not positively update on women's relative returns to using phones, the longer-term prospects of a program like SKY to boost smartphone engagement are unclear.

Indeed, over the long run —nearly 5 years after SKY phone distribution —households in program and non-program areas converged to nearly identical levels of smartphone ownership and use. Although treated households reported that the majority of program phones had broken, households in SKY-eligible communities were still 5.2 percentage points more likely to own a SKY phone. However, they were not more likely to own a smartphone overall, even though SKY areas did still have better internet connectivity, measured by average download speeds that were 17 percent faster. The lack of impacts at the household level reflects, in part, rapid adoption of phones: in non-SKY areas, 84 percent of households across the state reported owning a smartphone, compared to 44 percent of households (in a different sample in the capital district) prior to SKY distribution. Crucially, SKY did not catalyze higher long-term female phone usage or differentially higher acceptance of women's phone use among either males or females – in the long run, gender gaps in smartphone ownership and use remain large and significant in both program and non-program areas.

Long-term effects are similarly limited when considering key aspects of digital engagement related to information access. In general, we see that women's awareness – whether about digital financial services (DFS) available in the community or information about Covid-19 and how to prevent it – is worse than men's, and SKY did not help close gender gaps. While SKY marginally improved men's awareness of DFS in their villages, it did not affect information about DFS apps or adoption of DFS. SKY also did not improve access to information about government schemes or economic opportunities; if anything, gender gaps worsen in that women were *less* likely to use phones in SKY areas to access information about government benefits, while male behavior was unchanged. Given SKY's lack of impact on information about Covid, we unsurprisingly find no differences in Covid-related vaccination

[3] Chiplunkar and Goldberg (2022a) examine data from 14 LMICs, finding that the arrival of 3G Internet increased women's labor force participation, and employment for both men and women, but women's movement into the labor market featured higher participation in self-employment and unpaid work, while men's was concentrated in increased wage work and self-employment with decreased unpaid work.

rates across SKY and non-SKY locations.

One area where we do see some lasting effects of SKY is in labor markets. Men in SKY areas were significantly more likely to report engaging in animal husbandry and salaried employment (for the latter, a 1.3-1.4 percentage point increases above a low base of 7.5-10 percent), while women were *less* likely to engage in self employment, casual non-agricultural labor, and government workfare. We do not, however, observe significant impacts on overall earnings for either gender, suggesting these sectoral shifts may have had limited welfare effects. These findings relate to other research documenting impacts of the Internet on labor markets (Chiplunkar and Goldberg, 2022b; Hjort and Poulsen, 2019), though we find no evidence of *gains*, perhaps due to the fact that smartphone access and use in non-SKY areas had caught up to SKY areas within 5 years.

The findings we present should be taken as preliminary; future analysis will delve more deeply into these results, explore additional outcomes, and explore additional data from key informant interviews to better understand village dynamics. We also aim to explore heterogeneity of treatment effects along a variety of dimensions relevant to SKY's impact on villages and specifically women – we conjecture that SKY may have had more lasting impacts in communities or social groups where smartphone adoption was less rapid, due to characteristics like remoteness or household-level economic constraints. We anticipate that this analysis will also help us better unpack the extent to which limited differences across locations reflects "catch-up" as all locations, regardless of program status, adopted mobile phones and gained access to mobile internet. That said, the overall message is clear: Without a clear rationale and means to maintain control of digital assets in the household, delivering female-targeted phones was insufficient to close digital gender gaps.

The rest of this paper proceeds as follows. In section 2 we provide detail on the rural Chhattisgarhi context and SKY program. Section 3 describes our approach to measuring the short-term impacts of SKY and results, Section 4 does the same for the long-term analysis, and Section 5 concludes.

2 Background: Chhattisgarh and Project SKY

Home to 25.5 million people, 40 percent of whom live in poverty, Chhattisgarh is one of India's poorest states (RBI, 2019).There is a great deal of spatial variation within the state, however – the central, more urban areas are relatively well-off, while individuals living in remote rural areas are substantially poorer and often belong to historically marginalized demographic groups known as scheduled castes and tribes (often described as "SC" and "ST" populations). Some remote areas also suffer from political extremist activity, perpetrated by a group called the Naxals.[4]

Motivated in part by a desire to improve information and connectivity in difficult-to-serve

[4]The Naxals descend from the Communist Party of India. In the past, Naxals have organized large-scale attacks, killing 76 individuals in a single incident in Chhattisgarh in 2010. The Naxals attempted to derail the 2018 and 2019 elections by calling for a boycott, holding demonstrations encouraging individuals to stay away from the polls, and detonating several improvised explosive devices at polling places.

areas, the government launched the SKY program in July 2018, aiming to distribute phones to the female head of household in all rural villages with a population of 1,000 or more, based on data from the most recent (2011) Indian Census. Smaller villages situated in local government units (Gram Panchayats, or GPs) with at least one qualifying village were also eligible. After population-eligible villages were enumerated, the government listed areas that did not have LTE (4G) network coverage and subcontracted tower construction to Reliance Jio, the telecommunications company that provided SKY SIM cards.

Overall, SKY was well implemented. We combine 2011 Indian Census data with administrative data from the program to evaluate adherence to program rules. Figure 1 graphs the first stage. Overall, compliance was very good: just 2 percent of population-ineligible villages received SKY, while 74 percent of eligible villages received the program. When distribution occurred, an average of 0.8 phones were distributed per household, close to the program's goal.

Figure 1: SKY Distribution by Village Population

Notes: Results from local linear regressions using SKY administrative data merged to the 2011 Indian Census. Maximum village population per Gram Panchayat is top-coded at the 99th percentile and bottom-coded at the first percentile.

3 Short-Run Effects of SKY

To study the short-run impacts of SKY on phone use and associated norms, we employ an event study spanning phone distribution, which took place between July and September 2018. The event study leverages baseline data from a separate randomized trial.

To select the sample for this trial, we used administrative data from the Chhattisgarh Infotech Promotion Society (CHiPS) and information from the Socio Economic and Caste Census (SECC) to identify villages and beneficiary households scheduled to receive SKY in rural villages in Raipur district, also home to Chhattisgarh's capital city. 424 villages in 377

Gram Panchayats (GPs) were (i) eligible for SKY per CHiPS records and (ii) could be matched to the SECC data.[5] Of these, 222 villages met our village selection criteria and 212 were selected to form the final village sample.[6] We then used SECC records to select households to enroll in the survey. To be eligible for inclusion, a household needed to have a female intended SKY beneficiary who was: (i) under age 40; (ii) married; (iii) listed in the SECC with at least two family member names (to facilitate identification during surveying). We also limited the sample to households with a single SKY beneficiary.

In each of the 212 villages, we interviewed 8 SKY beneficiary women (6 literate and 2 illiterate) and their husbands. Surveys covered demographics and socio-economic status, phone use and ownership, beliefs and norms governing women's phone use, measures of women's empowerment, and social networks.

We randomly assigned villages to survey dates either before or after their scheduled SKY distribution date, with surveys conducted in all villages within six weeks of the distribution date. On average, we visited pre-distribution households 17 days prior to SKY and post-distribution households 19 days after SKY. Since randomization ensures predetermined characteristics in pre- and post-SKY villages are balanced, the key identifying assumption for our event study is that – absent SKY – there would have been no time variation in average outcomes of interest during the short study window. This allows us to interpret the effects we see as causal.

3.1 Data and Sample Characteristics

Table 1 provides an overview of the demographic characteristics for the couples we interviewed. Relative to their husbands (see panel C), women are 4.7 years younger and have 1.6 years less education. Nearly a third of the sample belongs to a marginalized social group (a scheduled caste or tribe), and 98% of households are Hindu. Relative to state-wide statistics on rural households from the National Family Health Survey (NFHS), our sample is relatively wealthy and less engaged in agriculture, with 16% owning a refrigerator, 26% owning a sewing machine, 53% owning a (motor) scooter, and 43% owning land. That said, household wealth is not high in absolute terms: 40-45% of individuals worked in household agriculture in the past year, and approximately 40% participated in the government's public works program for low-income households, known as NREGS (not shown in Table 1).

Overall, pre and post-distribution households are similar, although women in post-distribution households are slightly less likely to be literate per our survey data (SECC literacy status is balanced between the two groups by construction), and married roughly half a year later than their pre-distribution peers, resulting in a lower marital age gap. Post distribution households are also slightly more likely to be Hindu, although again these differences are quite small in absolute terms (1.3 percentage points) given the near universal share of Hindus in

[5] Just two SKY-eligible villages could not be matched to SECC codes.

[6] The sample was restricted to villages with more than 50 and fewer than 375 SKY beneficiaries, and villages were dropped if they did not include at least 36 literate and 12 illiterate women (who comprised our primary sample and a "buffer" sample if the original woman could not be reached). We also excluded 10 villages that we used to pilot our intervention.

this sample.

Table 1: Demographic Characteristics

	Pre-Dist. Mean (1)	Post Dist. (2)	N (3)
Panel A: Individual Characteristics of Eligible Women			
Age	33.823	0.442	1688
Can read or write	0.672	-0.043**	1696
Highest grade completed	4.914	-0.185	1690
Age married	16.934	0.445***	1580
Lives in natal village	0.038	0.005	1696
% from replacement sample	0.354	0.000	1696
Panel B: Individual Characteristics of Husbands			
Age	38.471	-0.036	1690
Can read or write	0.791	0.025	1696
Highest grade completed	6.500	-0.062	1696
Panel C: Household/Couple Characteristics			
Husband-Wife age gap	4.660	-0.492***	1685
Husband-Wife education years completed gap	1.587	0.120	1690
Household member count	5.656	-0.088	1696
Number of kids	2.693	-0.016	1696
Owns land	0.428	0.021	1696
Owns refrigerator	0.160	0.004	1696
Owns sewing machine	0.263	-0.021	1696
Owns scooter	0.527	0.000	1696
Hindu	0.982	0.013**	1696
% Scheduled caste	0.273	-0.014	1690
% Scheduled tribe	0.034	0.011	1690

* $p \leq 0.10$, ** $p \leq 0.05$, *** $p \leq 0.01$. Column (1) lists the pre-distribution mean and Column (2) lists the coefficient on Post from a regression of the outcome variable on Post along with replacement sample, block, and female literacy (obtained from SECC data) fixed effects. Standard errors are clustered at the village level.

Fortunately, these differences are relatively small compared to pre-distribution means. We assess robustness of results to controlling for these baseline imbalances in Appendix tables; results are qualitatively the same when including these controls.

3.2 Empirical Approach

To study the short run effects of SKY by gender, we estimate the following regression equation:

$$Y_{ivb} = \beta_0 + \beta_1 Post_v + \beta_2 Women_{ivb} + \beta_3 Post \times Women_{ivb} + \gamma_{ivb} + \mathrm{B}_b + \varepsilon_{ivb} \quad (1)$$

where Y_{ivb} is the outcome of interest for individual i in village v located in block b[7], $Post_v$ is a dummy that equals one if the respondent lived in a village randomly selected to be interviewed after the SKY phone distribution, and $Women_{ivb}$ is a dummy variable identifying female respondents. γ_{ivb} is a dummy that indicates whether the respondent was one of the 8 originally sampled for the survey or was drawn from the pool of replacement households due to difficulty reaching or scheduling a time with the originally targeted respondent. B_b is a vector of block fixed effects. This specification lets us simultaneously assess the impact of SKY on men (β_1), the impact on women ($\beta_1 + \beta_3$) and the impact on gender gaps (β_3). For some outcomes, including results on phone ownership below, we instead run gender-specific or household-level regressions that omit the female dummy and its interaction with $Post_v$. We cluster standard errors at the village level, the level at which SKY and survey timing (with respect to SKY implementation) were assigned.

3.3 Results

3.3.1 Phone Ownership

SKY was implemented with very high fidelity in this sample – over 98 percent of women in post-distribution villages reported they personally received a phone via the program. In Table 2, we study how this impacted rates of phone ownership, both by gender and at the household level.[8] Before distribution, 94% of households reported owning at least one phone of any type; SKY increased ownership by 6 percentage points, achieving universal phone coverage at the household level. While this value is high, column 4 shows that phones were primarily basic phones – only 44% of the households reported owning a smartphone prior to distribution.

Rates of individually-reported phone ownership, in columns 2 and 3, highlight that pre-distribution household ownership was driven primarily by men. Before SKY, 76% of men we interviewed owned a phone – a rate three times higher than that of women. Similarly, 21% of men interviewed owned a smartphone, while only 5% of their wives did.

[7] Blocks are the unit of governance between the gram panchayat and district.

[8] Household-level statistics include ownership by other individuals in the household who were not interviewed, such as children and parents.

Table 2: Short-Term Impacts of SKY on Phone Ownership

	Any phone ownership			Smartphone ownership		
	Household (1)	Men (2)	Women (3)	Household (4)	Men (5)	Women (6)
Post	0.060*** (0.009)	0.041* (0.022)	0.446*** (0.024)	0.551*** (0.019)	0.170*** (0.022)	0.559*** (0.024)
Pre-Dist Mean	0.939	0.764	0.236	0.440	0.209	0.048
N	1696	1696	1696	1696	1696	1696

Specification includes replacement sample, block and female literacy fixed effects. Standard errors clustered at the village level and reported in parentheses.

While nearly all women post-distribution reported personally receiving a phone from SKY, reports of phone ownership post-distribution show that many women did not retain ownership, even over a matter of weeks. Distribution increased women's smartphone ownership by 56 percentage points (column 6), implying that roughly 40% of women received a phone but transferred ownership to someone else. In fact, roughly a third of post distribution women reported owning no phone at all. At the same time, men were 17 percentage points more likely to report owning a smartphone after distribution, and 4 percentage points more likely to own any phone at all.

These results highlight the pitfalls of attempting to gender-target distribution of movable, valuable assets – while some households may respect intended ownership rights, others may not. Nevertheless, the program made substantial progress addressing gender gaps in phone ownership, at least over the short term. The gender gap in overall phone ownership reduced from 52 percentage points to 11 percentage points, while the increase in women's phone ownership was so large that the smartphone gender gap *reversed*, going from 16 to -23 percentage points. Notably, for many women the SKY phone was their first personally-owned phone.

3.3.2 Phone Use

While increasing women's ownership is an important first step, ensuring this ownership translates into productive use is essential for realizing socioeconomic benefits (Barboni et al., 2018). Table 3 displays men's and women's recent phone use as measured by an index of phone-related tasks undertaken in the past week, broken down by basic and "smart" uses.[9] Indices here are normalized to the male pre-distribution mean with a standard deviation of one and utilize a generalized least squares (GLS) weighting procedure to optimize information extracted and efficiency of estimates created from index variables (Anderson, 2008).

Post-distribution increases in phone usage for male respondents are sizable and significant,

[9]Basic uses include dialing calls, receiving calls, and sending/receiving SMS. Smart uses include using WhatsApp, taking photos, taking video, and using mobile internet.

at 0.147 standard deviation units (SDUs) for basic tasks and 0.348 SDUs for smart tasks, echoing the program's rapid and large impact on smartphone access. The second row in the table highlights how, prior to phone distribution, women's phone usage was markedly lower than that of men's, by approximately 0.4 SDUs for both types of usage.

Table 3: Short-Term Impacts of SKY on Phone Use

	Basic tasks index (1)	Smart tasks index (2)
Post	0.147***	0.348***
	(0.047)	(0.049)
Women	-0.425***	-0.390***
	(0.035)	(0.031)
Post x Women	-0.032	-0.157***
	(0.050)	(0.048)
p-value: Post + (Post x Women) = 0	0.003	0.000
Pre-Dist Mean [Men]	0.000	0.000
N	3389	3385

Outcomes in columns (1) and (2) are standardized indices of basic and smart phone tasks. All indices created following Anderson (2008) and indexed against the men in the pre-distribution villages. Specification includes replacement sample, block and female literacy fixed effects. Standard errors clustered at the village level and reported in parentheses.

While SKY also increased women's performance of both basic and smart tasks (see p-values in the table, which assess significance of the total effect of the program for women), gender gaps in smartphone use actually *grew*. This is reflected by the fact that SKY's impact on smart tasks is 0.157 SDUs lower for women as compared to men (significant at the 1 percent level); conversely, SKY left the gender gap in basic tasks unchanged – this suggests that women may have either had more limited ability to engage with smartphones (due to digital literacy gaps or social norms) or lower perceived returns to "high value" tasks like searching the web and consuming online content.

Both the ownership and usage results highlight a central concern with policies like SKY that target women with transferable assets: Other members of the household with higher perceived returns may appropriate the assets, potentially exacerbating gender gaps. This pattern is not unique to SKY – a similar phenomenon is apparent in recent work on cash grants and microfinance loans, which may be given to women, but used by male business owners in the household (Bernhardt et al., 2019). Of course, women might just be slower to experiment with the new phones, meaning gender gaps will close over time. In section 4, we provide evidence on the longer-term effects of SKY in order to understand the full picture.

3.3.3 Phone Use Norms and Beliefs

There are several channels through which SKY may have affected norms and beliefs about women's phone use: for example, citizens may positively update their beliefs in response to implicit and explicit government messaging that women should use and receive phones; women's increased use of and experimentation with phones may liberalize norms through a learning channel; or, beliefs could become more conservative if men enforce gender norms to secure control of the new phones.

In our survey, we asked both female and male respondents whether they thought it was appropriate for women to use a phone whenever she wanted/without supervision. We asked this question separately by a woman's marital status since norms around phone use tend to differ pre and post-marriage (Barboni et al., 2018). Means in the fourth row of Table 4 shows low rates of approval: Only 15.6 and 22.2 percent of pre-distribution males agree it is appropriate for unmarried and married women, respectively, to use a phone without supervision. Pre-distribution (row two), beliefs about phone use were very similar among men and women. After distribution, both genders liberalized their beliefs to a similar degree, with limited liberalization related to unmarried women's use, but a 6.1 percentage point increase in respondent reports that it is appropriate for married women to use phones.

Table 4: Short-Term Impacts of SKY on First Order Beliefs Around Women's Phone Use

	___ thinks it is appropriate for ___ to use phone:		
	Respondent; Unmarried women	Respondent; Married women	Disagrees that men have more uses for a phone
	(1)	(2)	(3)
Post	0.027	0.061^{***}	-0.087^{***}
	(0.018)	(0.021)	(0.023)
Women	-0.027^{*}	0.029	0.044^{*}
	(0.015)	(0.022)	(0.023)
Post x Women	0.006	0.006	0.113^{***}
	(0.023)	(0.030)	(0.033)
p-value: Post + (Post x Women) = 0	0.052	0.004	0.291
Pre-Dist Mean [Men]	0.156	0.222	0.313
N	3358	3355	3357

Specification includes replacement sample, block and female literacy fixed effects. Standard errors clustered at the village level and reported in parentheses.

Of course, women's ownership and use of phones in a low-income setting like ours will not just be determined by beliefs about propriety of phone use. Since most households did not have a smartphone before SKY, the phone was a scarce resource, which households might seek to allocate to the highest perceived return use. To understand impacts on perceived returns (which could evolve either due to strategic motives, or via learning), we asked both men and women whether they agreed with the statement "men have more use for a phone than women do". We code this question in table 4 such that a positive coefficient signals more female-egalitarian views. Column 3 shows that pre-distribution, women report more egalitarian views than men, though the gap is relatively small. (Only 31.3% of men disagree that men have more use for a phone than women, compared 35.7% of women). SKY *decreased* the share of men disagreeing by 8.7 percentage points, while disagreement (insignificantly) *increased* among women by 2.6 percentage points, more than tripling the gender gap in perceived returns. The fact that men and women update differently (especially despite similar changes in perceived appropriateness) suggests that some of these changes may represent a strategic effort of men to secure phones, contributing to the growing gender gap in smartphone use.

Taken together, our event study analysis indicates that SKY achieved its proximate goals of distributing phones to women, while connecting households to smartphones (and therefore mobile internet). In the short term the program was very successful at closing the gender gap in smartphone *ownership*. Progress further down the causal chain is less clear – while gender norms around the *appropriateness* of phone ownership liberalized among both men and women, men increasingly felt they had higher returns to phones than their wives; and while SKY increased women's engagement with smartphones, the gender gap in smartphone-related use increased. These patterns could, of course, shift over time – especially if women simply need more time to learn new skills and catch up to men. We now turn to our regression discontinuity study to assess these long-run impacts.

4 Long-Run Effects of SKY

4.1 Empirical Approach

In order to study the longer-term effects of SKY, we exploit the program's eligibility rule: All GPs that had at least one village with a population of 1,000 or more based on 2011 Indian Census data were SKY-eligible, while GPs where the largest village had a population of 999 or less were not. To answer our research questions, we conducted a detailed survey from January through July 2023 in 687 GPs (1,579 villages) in a narrow window around this discontinuity, permitting a regression discontinuity-based evaluation of the program.[10]

[10]Table A2 in the appendix explores differences in pre-determined characteristics across our short-term and long-term survey respondents. Short-run respondents tend to be slightly older and are more likely to be married than the general population, a design feature of the short-run survey, since only married respondents were surveyed. Likely reflecting age differences, short-run respondents have slightly lower education. Finally, long-run respondents are more likely to be part of Scheduled Tribe populations, and less likely to be part of Scheduled Castes, features in keeping with population-level demographics across Raipur and the rest of the state. (See table A3 for more population-level information from recent Demographic and Health Surveys.)

There are two different approaches to regression discontinuity analysis. The first, more common, "continuity" approach is based on the assumption that there is (counterfactually) a smooth, continuous relationship between the running variable (in our case, the population of the largest village in a GP) and the outcome of interest (Cattaneo et al., 2019). There are two downsides to this approach in our setting: first, the theoretical underpinnings of the continuity approach require that the running variable be continuous, while population is discrete. Second, this approach can have limited power and be sensitive to bandwidth choices. The second approach, which is uniquely well-suited to our setting, is the "local randomization" method described in Cattaneo et al. (2023). The theoretical justification for this approach is different: Essentially, the analyst must be willing to assume that there exists a window around the discontinuity in which the outcome of interest is unrelated to the running variable. Put another way, one must assume that in a small window around our cutoff, population is as good as randomly assigned. This approach was viable in our setting as (a) we had access to a significant number of GPs with a largest village population very close to 1,000 and (b) we had access to 2011 Census data, which allowed us to algorithmically select a population-based window around the cutoff in which the local randomization assumption was empirically justified.

4.2 Sampling and Data

To form the sample, we first decided to focus on 18 of Chhattisgarh's 33 districts with high rates of SKY implementation. (Figure 2 highlights selected study districts).[11] Table A3 in the appendix uses Demographic and Health Survey data to explore the ways in which households in these sample locations compare to rural areas in the rest of the state and households in rural Raipur. The primary difference across these locations is that areas covered by both the long-run survey tend to have lower Scheduled Tribe representation. Non-study area households are also more likely to own land. While these differences do not call into question the main results of the study, we intend to explore heterogeneity by social group in future work to assess whether the impacts of SKY in other parts of Chhattisgarh may differ based on their larger Scheduled Tribe representation.

On average, around 79 percent of the eligible GPs in these districts had received SKY phones. Within these 18 districts, we used the algorithm suggested by Cattaneo et al. (2023) to select the relevant population window around our discontinuity.[12] This returned a window with

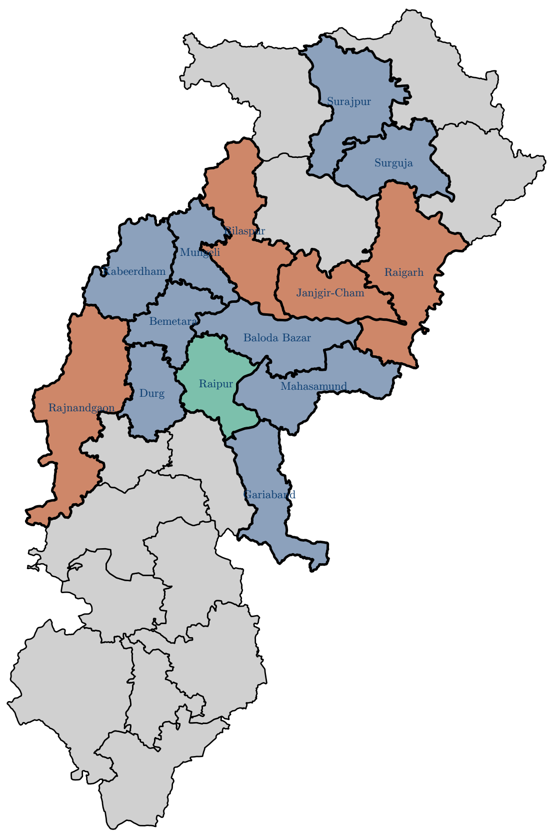
[11]We excluded the capital district of Raipur, since we had conducted a randomized controlled trial in 212 SKY eligible GPs there.

[12]The algorithm works as follows. First, the analyst identifies a set of "baseline" characteristics on which balance is desired. We selected average household size, fraction population female, fraction population scheduled caste, fraction population scheduled tribe, landholding area in hectares per household, number primary schools per 1,000 households, number middle schools per 1,000 households, whether the GP has at least one village unconnected to a tarmac road, land area sown per household, whether the GP has mobile coverage, has a post office, has bus service, has self-help groups, has a bank or co-op, and has a fair price shop (where subsidized food can be purchased), all measured in the 2011 Census. We also included a dummy variable identifying GPs affected by left-wing extremism. Then, we started with a window of ± 10 around the population discontinuity and performed a test (via randomization inference) of whether these characteristics were balanced above/below the discontinuity. If the test returned a p-value of 0.15 or more, we widened the window by 1. We repeated this process until the joint test returned a p-value less than 0.15. The

GPs with population of 1,000 ±99, yielding a survey sample of 687 GPs. 279 of the GPs in this sample are "treatment" units, where the largest village had a population ranging between 1,000–1,099 and the remaining 408 GPs are "control" units where the largest village had a population between 900–999 people. Figure 2 highlights the study districts.

In selected GPs, we randomly sampled 15 women aged 18-45 from the universe of individuals listed on the voter rolls associated with polling booths within the GP; we then attempted to survey the woman and a randomly selected male household member.

Figure 2: Map of Study Areas



Notes: This map uses a district-level shapefile as of 2018/19 to illustrate study areas. Raipur, the capital district and the site of our short-run effects study, is depicted in teal. Several districts were split in 2020 and 2022—as a result this map highlights (in orange *and* blue) 13 study districts, the count as of 2018/19; as of 2023 our study covered 18 districts, with the 5 new districts that had been carved out of the original blue districts depicted in orange.

We surveyed respondents in 684 out of the selected 687 villages, excluding 3 GPs due to safety concerns related to left-wing extremism. Table A1 reports differences between treatment

selected window is the largest window with a p-value greater than 0.15, meaning the locations within the selected sample are statistically indistinguishable. While some GPs in Chhattisgarh have only one village, we restricted our potential sample to GPs with more than one village since we found evidence of imbalance across the SKY threshold in single-village GPs when implementing the selection algorithm. Prior to running the algorithm we also excluded 25 GPs in which we had piloted our survey.

(SKY eligible) and control (SKY ineligible) GPs per the 2011 Census. Overall, the two groups are very similar, which is by design given our selection algorithm.

Household Surveys: In each GP, we attempted to survey 15 female and 15 male respondents. To do this, we used voter rolls to randomly sample a female from the ages of 18 to 45 as the focal respondent. At the time of surveying, an adult household member was asked for a list of male members of the household between the ages of 18 and 50.[13] The male respondent's name was randomly selected from the provided list of male members to serve as the focal male.

We also randomly selected 100 non-sampled women as our replacement sample, placing them in random order. We utilized the replacement list if any of the 15 sampled women were unavailable, did not consent to the survey, did not live in the village anymore, or were outside our target age range of 18-45. If we were unable to survey a household male from a female respondent's household, we also used our replacement list to identify a household with an age-eligible female respondent. We then surveyed an adult household member, confirming the woman's eligibility and gathering information on survey-eligible male household members. We then randomly selected one of these males as the replacement male respondent. Using this process, we surveyed 10,282 female and 10,277 male respondents; 70% of individual respondents lived in a household where we surveyed a respondent of another gender.

Key Informant Interviews: We also conducted key informant surveys to collect data on community-wide outcomes. To understand the economic activities in the largest village (as per the 2011 Census) within each sample GP, we identified and surveyed "village criers" (a person hired by village heads to go door-to-door to relay information) and ward members (elected representatives on the village council) as the most informed individuals in the GP. We also surveyed at least one health worker per GP.[14] Lastly, we identified and surveyed a leader of Self-Help Groups (SHG) in every GP for a module on village-level SHG participation. In total, we interviewed key informants in 682 sample GPs out of the planned 687. [15]

4.3 Empirical Specification

Given the local randomization identification assumption, we run ordinary least squares (OLS) regressions, leveraging the full set of surveyed GPs and including district fixed effects. The pre-specified fixed effects are intended to improve statistical power by holding constant district-level variation that might be related to our outcomes of interest. Our main analysis will focus on intent to treat (ITT) effects, meaning we count any location as a SKY

[13]99.75% of our male sample is between 18-50 years old.

[14]We surveyed either the Accredited Social Health Activist (ASHA), locally known as the Mitanin, or an Anganwadi Worker for health information. Both are goverment-supported community health workers that facilitate access to healthcare, with the Anganwadi worker focusing on care for mothers and young children in the community out of a local center.

[15]We surveyed 514 village criers, 899 ward members, 698 ASHA, 16 Anganwadi workers, and 703 SHG leaders and members in total. We have at least one female key informant in every GP, and at least one male key informant in 594 GPs (i.e. there are 88 GPs with only female informants).

location if the locality was *eligible* to receive the full program (by falling within the population requirements), whether it actually benefited from the program or not. We detail this empirical approach, as well as our planned outcomes of interest in a pre-analysis plan posted on the Registry for International Development Evaluations.[16]

Formally, the regression specification is:

$$Y_{ig} = \beta_0 + \beta_1 \mathbb{1}\{pop_g \geq 1000\} + \delta_d + \varepsilon_{ig} \tag{2}$$

where Y_{ig} is the outcome of interest in GP g for individual i, pop_g is the 2011 Census population of the largest village in GP g, δ_d is a vector of district fixed effects, and ε_{ig} is the error term. We cluster standard errors at the GP level since this is the level at which "treatment" (SKY eligibility) was assigned. In order to study treatment effects for men and women at once (as well as gender gaps and treatment effects on gender gaps), we use a second specification, which stacks male and female responses and augment equation 2 to include a dummy variable identifying women and its interaction with the SKY eligibility dummy. In this case, the coefficient on SKY represents the effect for males, the coefficient for SKY interacted with a female dummy is the difference across genders in the effect of SKY; we also present p-values from a test of whether the total effect of SKY for women is different from zero, similar to our approach in the short-run analysis.

4.4 Results

4.4.1 Respondent Characteristics

Table 5 provides descriptive information about respondents in our survey. By design, half of the respondents are female, and individuals are relatively young, with an average age of approximately 33-34 years. Even so, education levels are relatively low – the average male respondent completed just under 8 years of education and the average female respondent has just under 6 years of education. Approximately 83 percent of males and 88 percent of females are married. Consistent with Chhattisgarh's demographic makeup, a significant share of our sample hails from a marginalized group – 31 percent from scheduled tribes and 16 percent from scheduled castes. All these characteristics are balanced across SKY and non-SKY GPs.

Comparing across our short-run (Raipur district) and long-run (state-wide) samples, the 2023 state-wide survey respondents live in more remote areas and exhibit some higher indicators of marginalization – e.g., they are nearly 30 percentage points more likely to belong to a scheduled tribe. Long-run survey respondents could be unmarried and therefore are slightly younger than the short-run survey respondents. Despite their potential social marginalization, long-run respondents are more educated on average than those in the short-term sample (recall enrollment in the short-run sample was stratified on literacy), and are more likely to own land.

[16]The study listing is available at https://ridie.3ieimpact.org/index.php?r=search/detailView&id=1243.

Table 5: Balance on respondent level characteristics

	Women			Men		
	Non-SKY Mean	Difference	N	Non-SKY Mean	Difference	N
	(1)	(2)	(3)	(4)	(5)	(6)
Age	32.175 [6.667]	-0.130 (0.141)	10282	32.382 [6.892]	-0.030 (0.144)	10277
% Married	0.883 [0.322]	0.004 (0.007)	10282	0.833 [0.373]	-0.011 (0.008)	10272
Years of schooling	6.184 [4.838]	-0.126 (0.112)	10246	8.297 [4.327]	0.080 (0.104)	10265
% Hindu	0.918 [0.274]	-0.003 (0.008)	9317	0.938 [0.242]	0.003 (0.007)	10097
% Scheduled Tribe	0.308 [0.462]	-0.015 (0.017)	9214	0.308 [0.462]	-0.008 (0.017)	9925
% Scheduled Caste	0.158 [0.365]	0.013 (0.015)	9214	0.154 [0.361]	0.006 (0.015)	9925
HH owns land	-	-	-	0.646 [0.478]	-0.007 (0.011)	10239
% from replacement sample	0.512 [0.500]	-0.014 (0.012)	10282	0.530 [0.499]	-0.022* (0.012)	10277

Standard Deviation reported in square brackets and standard errors in parentheses. Specification includes district fixed effects. Standard errors clustered at the GP level. Refusals are missing.
***$p\leq0.01$, **$p\leq0.05$, *$p\leq0.10$

4.4.2 First Stage

While we selected our sample from GPs where SKY was implemented with high fidelity, we still check the "first stage" measured by self-reported receipt of the program. This question was only asked of men, with results presented in the first column of Table 6. Very few men in control GPs (less than 3 percent) reported that their household received a SKY phone, with self-reported receipt 56 percentage points higher in SKY-eligible areas. Given the ≈ 4.5 year recall period, this suggests the program was both salient and well implemented, in line with records from administrative data.

In column 2, we study long-run impacts on current ownership of SKY phones. Essentially no one in the control group reported current ownership, with a 5.2 percentage point treatment effect. When we asked beneficiary households why they no longer had a SKY phone, 95 percent reported that the phone had broken, and 5 percent reported the phone was lost. Thus, we estimate the impact of SKY after the initial asset had (in most cases) depreciated.

Table 6: Impact of SKY on Phone Ownership and Access

	(1) Got a SKY Phone	(2) Currently Owns a SKY Phone	(3) # of button phones	(4) # of smart phones	(5) Household has any smart phone
SKY Eligible	0.56***	0.052***	-0.053***	0.018	0.0088
	(0.017)	(0.0042)	(0.014)	(0.025)	(0.0081)
Control Mean [non-SKY]	0.028	0.0030	0.48	1.46	0.84
Observations	10274	10267	10275	10275	10269

All responses are from the male survey. Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parentheses. Refusals are recoded as missing. Missings due to skip patterns recoded to 0.

In addition to phone distribution, the program initiated the construction of mobile phone towers, which could have led to better network connectivity in eligible GPs. In each GP, our enumerators were tasked to conduct at least one speed test with a Jio SIM card. Jio was the service provider that partnered with SKY in building mobile towers, so all SKY SIMs were from Jio. Enumerators used their own phones to conduct these speed tests. In some villages, the speed test website failed to load and hence those villages are missing from our data. On average, download speeds were higher in SKY-eligible villages by around 1.52 Mbps (17 percent), while upload speeds remained unchanged. Our conclusions are qualitatively similar when focusing on the SKY-linked mobile network operator (Jio) only (columns 3 and 4), or restricting to the fastest logged speeds in a given locality (columns 5 and 6). We find no impact on upload and download speeds from other mobile internet providers (Appendix Table B4). Thus, SKY had lasting effects on the quality of mobile connectivity in program GPs.

Table 7: Impact of SKY on Internet Speeds

	All		Reliance JIO only		Fastest	
	(1) Avg. download speed	(2) Avg. upload speed	(3) Avg. download speed	(4) Avg. upload speed	(5) Max. download speed	(6) Max. upload speed
SKY Eligible	1.52***	0.30	1.63**	-0.025	2.61**	0.27
	(0.58)	(0.36)	(0.65)	(0.34)	(1.20)	(0.84)
Control Mean [non-SKY]	8.78	3.03	9.48	2.92	20.9	8.37
Observations	682	682	677	677	682	682

Results from a GP-level regression displayed. Since enumerators conducted at least 1 speed test in every GP, we average across all data points within each GP to calculated the average speeds in column (1)-(4). Outcomes in columns (1)-(2) denote the average upload and download speeds across all types of service providers and speed tests in a GP. Columns (3)-(4) denote average upload and download speeds for Reliance JIO simcards in a GP. Finally, columns (5)-(6) denote the fastest upload and download speed across all service providers and tests in a GP. Upload and download speeds are in Mbps.

Lower long-term ownership of SKY phones is not unexpected given the long elapsed time between phone distribution and the follow-up survey. However, we also anticipate that the introduction of mobile internet and phones may have fundamentally increased engagement with mobile technology beyond that enabled by the initial phone, particularly since we have evidence of longer-term better mobile internet connectivity in SKY locations. We next return to columns 3-5 of Table 6 to assess whether SKY had lasting effects on household-level phone ownership. This could be the case if, for example, the SKY phone catalyzed greater demand for smartphones in treated households. We find no evidence of such effects – the only significant impact is a 0.05 unit reduction in the number of button phones per household (a modest decline relative to the control mean of 0.48, which could suggest SKY phones substituted for basic phones following distribution). However, it is worth noting (as seen in columns 4 and 5) that the average control group household had 1.46 smartphones in 2023, with 84 percent of households owning at least one phone. This is striking given that just 44 percent of households in our 2018 Raipur study (on average a richer, better-connected area) owned a smartphone pre-SKY. Taken together, these results suggest that SKY was implemented in an environment with rapid adoption of smartphones, and failed to make a dent in long-term phone ownership beyond that seen elsewhere.

Even if SKY had no lasting effects on household phone ownership, it could still matter for female phone ownership and autonomy, through either a norms effect and/or a learning/demand effect. In Table 8, we investigate SKY's long-run impact on gender gaps by studying the impact of SKY on both men's and women's phone use.

For this analysis, in line with the short-term event study, we constructed two GLS-weighted phone use indices: The first is a basic task index that involves calling and texting (SMS). The second is a smart task index which covers the use of popular applications like WhatsApp, and taking photos and videos. All indices are again calculated following Anderson (2008); here, the outcome variables are indexed against men in non-SKY (control) GPs.

Row 2 in table 8 highlights how women across treatment and control villages are much less likely to be using the phone than men across all categories of tasks. Rows 1 and 3 show that SKY had no impact on recent basic or advanced tasks, regardless of respondent gender. Appendix tables B2 and B3 display index components and suggest SKY did not spur certain types of phone-based activities and not others. Only one coefficient of the 10 activities is marginally higher due to SKY overall, and there are no types of higher usage among women. (In fact, coefficients suggest, if anything, differentially lower usage among SKY women for smartphone-relevant activities.)

In column 3, we study impacts on women's access to phones, measured via a GLS-weighted standardized index summarizing women's phone ownership, her "primary phone user" status, ability to use a phone without permission, and use of a phone outside the home. Here again we see no impact of SKY on this index of phone access.

These results echo patterns in our short-run survey – gender gaps in phone use have persisted despite the rapid adoption of new phone technologies. What is more, SKY had no impact on the gender gap – in fact, point estimates suggest a worsening of the gap; male phone use is slightly (not significantly) higher in SKY areas for smart tasks, while female phone use is slightly lower.

Table 8: Impact of SKY on Phone Use

	(1) Basic Tasks	(2) Smart Tasks	(3) Female Phone Access Index
SKY Eligible	-0.015	0.010	0.0089
	(0.021)	(0.022)	(0.023)
Women	-0.47***	-0.61***	
	(0.017)	(0.015)	
SKY Eligible × Women	-0.0096	-0.022	
	(0.026)	(0.024)	
p-value: SKY + SKY × women	0.22	0.39	-
Control Mean [non-SKY men]	0	0	0
Observations	20544	20550	10281

All phone use indices are created following Anderson (2008) and indexed against the men in non-SKY-eligible GPs. Column (3) compiles responses to four survey questions about women respondents' ownership and access to smartphones in their household. This is indexed against women in non-SKY-eligible GPs. Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parentheses. Refusals are recoded as missing. Missings due to skip patterns recoded to 0.

4.4.3 Phone Use Norms

So far, we have seen that SKY's positive impacts on phone ownership and use were transient. In Tables 9 and 10, we check persistence of treatment effects on gender norms around phone use.

Table 9 studies impacts on both respondents' own attitudes towards women's phone use (column 1 for appropriateness of use among unmarried women; column 3 for appropriateness of use among married women) and respondents' beliefs about their spouse's opinion.[17] Overall, attitudes are relatively conservative, with just 36 and 51 percent of control group men reporting unmarried and married women's phone use is appropriate. Women are slightly (2 and 5 percentage points) more likely to view use as appropriate, and spousal perceptions are reasonably accurate, with both men and women slightly under-estimating their partner's support. (Note, however, that these rates of acceptance are higher than those in the short-term results.) We find that SKY had no lasting impact on these attitudes, and no impact on gender gaps in support for women's phone use.

[17] Respondents were asked: "Think about an (un)married woman in this village from your social group who has her own phone and uses it whenever she wants. In your opinion do you think it is appropriate or inappropriate? Would your spouse think it is appropriate or inappropriate?"

Table 9: Impact on First-Order Beliefs Around Women's Phone Use

	_____ thinks it's appropriate for _____ to use phone:			
	(1) Respondent: Unmarried Women	(2) Spouse: Unmarried Women	(3) Respondent: Married Women	(4) Spouse: Married Women
SKY Eligible	0.0055	0.0091	0.0043	0.0032
	(0.011)	(0.012)	(0.011)	(0.012)
Women	0.023***	-0.021**	0.051***	-0.011
	(0.0087)	(0.010)	(0.0092)	(0.011)
SKY Eligible × Women	0.0016	0.0033	0.0035	0.0045
	(0.014)	(0.015)	(0.015)	(0.016)
p-value: SKY + SKY × women	0.50	0.26	0.47	0.50
Control Mean [non-SKY men]	0.36	0.36	0.51	0.50
Observations	20332	17040	20347	16997

Columns (2) and (4) are limited to those respondents who are currently married and excludes never-married, divorced, separated, and widowed respondents.
Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parentheses. Refusals are recoded as missing. Missings due to skip patterns recoded to 0. Don't knows are recoded as 0.

Table 10 studies impacts on second order beliefs, or perceived norms. For each of unmarried and married women's phone use, we separately asked respondents how many women and men (out of 10) in their community would approve of women's phone use. Again, we find evidence of relatively conservative beliefs that are slightly more liberal among women. SKY had no impact on beliefs of either gender.

Table 10: Impact on Appropriateness of Second-Order Beliefs Around Women's Phone Use

	The number of _____ that think it's appropriate for _____ to use phone:			
	(1) Community women: Unmarried women	(2) Community men: Unmarried women	(3) Community women: Married Women	(4) Community men: Married women
SKY Eligible	0.0038	0.057	-0.056	-0.062
	(0.063)	(0.063)	(0.089)	(0.089)
Women	0.38***	0.23***	0.36***	0.16**
	(0.052)	(0.058)	(0.077)	(0.079)
SKY Eligible × Women	0.034	-0.12	0.15	0.17
	(0.086)	(0.087)	(0.12)	(0.12)
p-value: SKY + SKY × women	0.53	0.26	0.26	0.18
Control Mean [non-SKY men]	4.59	4.24	4.96	4.71
Observations	20434	20430	10277	10272

Responses limited from 1 to 10. A higher response means they believe more people think the activity is appropriate.
Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parentheses. Refusals are recoded as missing. Missings due to skip patterns recoded to 0. Don't knows are recoded as 0.

Given SKY's long-run lack of lasting impact on household-level phone ownership, women's phone access, phone use among both genders, and norms, we anticipate impacts on other downstream outcomes are also unlikely. We verify this hypothesis in the following subsections.

4.4.4 Digital Financial Services (DFS)

India has emerged as a global leader in financial inclusion, opening more than 460 million bank accounts under the Pradan Mantri Jan Dhan Yojana program.[18] This, coupled with the spread of smartphones to rural areas, has laid a foundation for new digitally-enabled financial services, including digital payments. Although digital payments are possible on basic phones, most digital payment services are generally accessed through smartphones in India, with limited access occurring via basic phones or other means. Even with treatment-control convergence in smartphone ownership and use, however, it is plausible that SKY gave rural DFS markets a jump start by spurring earlier adoption and better network access.

Indeed, in Table 11, we see that there is ample room for DFS to grow in control areas. While 77 percent of control group men are aware of DFS apps and 60 percent know of shops in the village that use DFS, just 28 percent report using a DFS app in the past year. Gender gaps are very large – with awareness 31-32 percentage points lower among women and use 23 percentage points lower. SKY's impacts are limited – we find a 2.3 percentage point increase in the likelihood that men are aware of DFS apps. This is only significant at the 10 percent level, however, so we interpret this result with caution. There are no differences by gender in SKY's impact on DFS knowledge and usage.

These findings are important from a policy perspective. While India's digital infrastructure is growing rapidly and our survey finds evidence of growing adoption in rural areas, this is almost entirely being driven by men, with women barely engaging with new technologies. The lack of SKY treatment effects further indicates that this challenge cannot be addressed by simply distributing smartphones to women.

Table 11: Impact of SKY on Use of Digital Financial Services

	(1) Knows Any DFS App	(2) Knows Village Shops Use DFS	(3) Ever Used DFS Apps	(4) Used DFS Apps In Past Year
SKY Eligible	0.0016	0.023*	0.011	0.0091
	(0.0098)	(0.013)	(0.010)	(0.010)
Women	-0.32***	-0.31***	-0.23***	-0.23***
	(0.0092)	(0.0094)	(0.0070)	(0.0069)
SKY Eligible × Women	0.0077	-0.013	-0.015	-0.014
	(0.014)	(0.014)	(0.011)	(0.011)
p-value: SKY + SKY × women	0.44	0.36	0.42	0.30
Control Mean [non-SKY men]	0.77	0.60	0.28	0.28
Observations	20553	20558	20559	20549

DFS Apps refer to smartphone applications such as PhonePe, BharatPe, GooglePay, PayTM, BHIM, and individual banks' apps. A break-down of activities conducted over DFS in Column (3) are in the Appendix in Table E1.
Specificatn includes district fixed effects. Standard errors clustered at the GP level and reported in parenthesis. Refusals are recoded as missing. Missings due to skip patterns recoded to 0.

[18] Economic Times, 2023

4.4.5 Employment and Income

Digital technology may provide access to information about economic opportunities or government programs. We therefore next ask whether SKY impacted respondents' ability to gather information related to income generation and government schemes, and whether it had an impact on paid labor and earnings. Table 12 reports results, first for information seeking (columns 1-4), then for income generation (columns 5-6). In columns 1 and 3, we focus on whether the respondent used their phone recently to access information about the stated category. In columns 2 and 4, the phone activity indices group together various ways the respondents use their phones (calls, SMS, internet) to gather information.

Table 12: Impact on Information on Income and Work

	Information on Income-Generation		Information on Government Schemes		Paid Work Index	
	(1) Used Phone	(2) Phone Activity Index	(3) Used Phone	(4) Phone Activity Index	(5) Past Year Index	(6) Past Month Index
SKY Eligible	-0.010	0.00088	0.0063	0.023	0.024	0.011
	(0.011)	(0.023)	(0.0096)	(0.022)	(0.025)	(0.025)
Women	-0.27***	-0.42***	-0.18***	-0.34***	-0.25***	-0.19***
	(0.0081)	(0.017)	(0.0074)	(0.016)	(0.019)	(0.019)
SKY Eligible × Women	0.0015	-0.016	-0.014	-0.052**	-0.087***	-0.078***
	(0.013)	(0.026)	(0.011)	(0.024)	(0.033)	(0.029)
p-value: SKY + SKY × women	0.22	0.18	0.19	0.0093	0.016	0.0075
Control Mean [non-SKY men]	0.40	0	0.28	0	0	0
Observations	20557	20557	20556	20556	20558	20558

All indices are calculated following Anderson (2008) and are indexed against the men in non-SKY villages. Columns (1)-(4) pertain to using phones for information on employment or income-generation activities in the past three months. Components of the two Phone Activity indices are in Tables F1 and F2 respectively. Columns (5)-(6) is an index of paid labor acitivities, explained in more details in Tables F3 and F4.
Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parentheses. Refusals are recoded as missing. Missings due to skip patterns recoded to 0.

In line with earlier results, we find large gender gaps and limited treatment effects on information-seeking. Women are less likely to use a phone to access information on income-generating activities and government schemes. For example, 40 percent of control men report using a phone to access information about economic opportunities; only 13 percent of women report the same. What's more, column 4 shows the gender gap in phone activity *increases* in treatment villages as SKY (insignificantly) increased men's use of phones to get information on government schemes, while significantly decreasing women's use of phones for the same. This result runs counter to the program's aim of connecting citizens to information from the government - the phones came with pre-loaded information and apps related to the incumbent government.[19]

In the last 2 columns of Table 12, we construct a paid work index that compiles binary indicators for different types of paid work done in the past year and month. Paid work includes agricultural labor, casual labor, work under the National Rural Employment Guarantee Scheme (NREGS), and others (more details are in the Appendix). Not only are women working less on paid labor relative to men in control areas (by 0.19-0.25 standard deviation units), but SKY worsens the gender gap by 0.077-0.088 standard deviation units, significant

[19] The government that ran the SKY program lost the election that occurred shortly after SKY was implemented. This may have disrupted the utility of the apps, which could have in turn deterred women from seeking further information about government services on their phones. We cannot, unfortunately, test this hypothesis directly.

at the 1 percent level. Moreover, the overall SKY treatment effect for women is *negative* and significant, with p-values of 0.015 and 0.008. Men, by contrast, are unaffected in terms of the overall index.

Appendix Tables F3 and F4 show that the relative reduction in female work is driven by reduced engagement in animal husbandry and self-employment. There is also some evidence of reallocation across sectors. Men in SKY-eligible communities are now more likely to engage in animal husbandry and salaried employment (which is generally more remunerative and difficult to find). SKY-eligible women are also marginally less likely to have participated in casual non-agricultural labor and NREGS work in the past month. Figure F1 shows that SKY did not, however, significantly shift the overall distribution of earnings for either gender.

With increased access to a SKY phone, treatment villages do not seem to seek out information on employment and government schemes at a higher rate. However, women in SKY-eligible villages perform relatively worse on the Paid Work Index, and SKY appeared to shift men and women across sectors, which suggests shifts to underlying household and/or labor market dynamics. We next dig deeper into community-wide labor and related market outcomes.

4.4.6 Community-level outcomes

In order to paint a more holistic view of local labor markets, we included a series of questions in our key informant surveys that asked about the ease of obtaining work and prevailing wage rates in different agricultural seasons (the high/monsoon season, called "kharif", and the low pre-kharif season where there is little agricultural work).

Table 13: Impact of SKY on labor market tightness

	Men		Women	
	(1) High season	(2) Low season	(3) High season	(4) Low season
SKY Eligible	0.030	-0.032	0.071	-0.017
	(0.059)	(0.059)	(0.057)	(0.060)
Control Mean [non-SKY]	0	0	0	0
Observations	1405	1402	1405	1403

Outcomes in columns represent indices constructed following Anderson (2008) and correspond to agriculutral and casual labor jobs in the high (Kharif season: July-October) and low season (pre-Kharif season: March-June). A positive value of the outcome represents tighter labor markets where jobs are easily available (higher vacancies) for workers looking. Refusals are missing. Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parentheses.

Table 13 focuses on measures of labor market tightness, which we elicited from key informants by asking how many (of 10) workers of a given gender would be able to find employment in different types of agricultural work (e.g. sowing, harvesting) in the high and low seasons. We standardize responses and combine them into season×gender of worker GLS-weighted indices. Higher values of the index indicate greater ease of finding work/tighter labor markets. Overall, we find no evidence SKY impacted labor market tightness in either season.

Table 14 looks at the effect on wages by gender. We asked the key informants what the prevailing daily wage rate was for agricultural wages in both seasons. There is a positive (but not significant) effect on wages in SKY-eligible villages for both men and women in the low season. This effect becomes negative for men and dampens for women in the high season. However, there are no statistically significant impacts of SKY on wages for either men or women across agricultural seasons, and coefficients are quite small compared to the mean wages in control areas.

Table 14: Impact of SKY on labor market wages across seasons

	Men		Women	
	(1) Low season wages	(2) High season wages	(3) Low season wages	(4) High season wages
SKY Eligible	1.52	-0.45	2.59	0.98
	(2.68)	(2.43)	(2.00)	(1.86)
Control Mean [non-SKY]	198.1	193.8	163.4	162.8
Observations	1391	1409	1393	1410

Table reports the treatment effect of SKY on the average nominal wages (INR) for men and women across seasons. Outcomes were constructed by averaging wages over the high (Kharif: July-October) season activities (harvesting, sowing, construction work) and low season (pre-Kharif: March-June) activities (agricultural work and construction work). Wage data was winsorized at the 1st and 99th percentiles. Refusals are missing. Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parentheses.

We look at the distributional effect of SKY in Figure D1 by plotting the density of going wage rates for men and women across seasons for both SKY and non-SKY GPs. Men's wages during the Kharif season have a smaller variance, and we cannot reject that these distributions for SKY and non-SKY GPs are statistically different. Women's wages, on the other hand, exhibit the opposite insight: there is negligible seasonal variation but we can conclusively infer that the wage distributions across SKY and non-SKY GPs are different: Women's wages are statistically higher in SKY areas than in non-SKY areas. This analysis is preliminary, however; we intend to explore this further to understand it better (both to verify robustness and interpret this alongside drops in women's participation in paid work) in future analysis.

Overall, we find suggestive evidence of some sustained effects on local labor markets, despite fade out in access to and use of phones. This raises the possibility that SKY impacted other aspects of local economic activity, which we consider in Table 15 by reporting treatment effects on the number of different types of local businesses.

Table 15: Impact of SKY on number of local businesses

	(1) Groceries & Pharmacy	(2) Clothing	(3) Manufacturing	(4) Services etc
SKY Eligible	0.10*	0.028	-0.074	-0.012
	(0.061)	(0.061)	(0.055)	(0.060)
Control Mean [non-SKY]	0	0	0	0
Observations	1411	1408	1411	1413

Outcomes displayed are standardized indices of the number of businesses (winsorized at the 99th percentile), which are constructed following Anderson (2008). Groceries & Pharmacy includes public, private groceries and pharmacy shops. Manufacturing includes kilns, mills, and small manufacturing firms. Services includes eateries, mobile recharge shops, and other businesses. Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parentheses.

Using data from the key informant survey, we find that SKY had no meaningful impact on the overall number of local businesses. There is some evidence of SKY bringing about a 0.1 standard deviation unit increase in the number of grocery and pharmacy stores (Table 15), which is primarily driven by SKY GPs having, on average, 0.5 more privately-owned grocery stores than non-SKY GPs. (Table D1). We caveat that our survey does not capture the intensive margin of business activity, which is another important channel through which SKY could have affected market-level outcomes.

4.4.7 Covid-19 Information Environment

In addition to impacting labor markets, SKY could have impacted the information environment. While SKY had no impacts on phone use at the time of our long-run survey, we cannot rule out the possibility that the program had sustained impacts in the medium run. This is important, as SKY arrived in communities approximately one year before the beginning of the Covid-19 pandemic, which had devastating economic and health consequences across India. Pandemic impacts were mediated in part through access to information to prevent infection and spread and encourage early vaccination. Yet misinformation about Covid-19 was widespread, partly driven by inaccurate social media posts. Even if SKY had no lasting impacts on consumption of different types of media (see Appendix Table G2), it could have affected Covid-19 beliefs in a persistent way given timing of the program and Covid-related information campaigns. In this section, we therefore explore respondents' knowledge of Covid-19 myths and realities.

To assess susceptibility to misinformation and access to true information, we elicited respondents' beliefs of the veracity of common Covid-19 rumors circulated on social media in the study area. Respondents were given a mix of 3 true and 4 false Covid-19-related statements and had to respond to each on a 5-point Likert scale that ranged from "completely true" to "completely false". We combine responses in a GLS-weighted standardized index, re-scoring outcomes so higher values always correspond to better information and present the results in Column (1) in Table 16. Overall, women score 0.15 standard deviation units *worse* on the information index. Inspecting results for the index components in Appendix Table G1 shows that this reflects the fact that women are more likely to believe both incorrect *and* correct statements about the disease. SKY had no impact on susceptibility to misinformation for either men or women, however.

Table 16: Covid-19 Information Environment and Sources of Information

	Information	Source		
	(1) Information Index	(2) Institutional Covid News Source Index	(3) Traditional Covid News Source Index	(4) Digital Covid News Source Index
SKY Eligible	0.0061	0.034	0.027	0.015
	(0.022)	(0.024)	(0.025)	(0.023)
Women	-0.15***	-0.088***	-0.16***	-0.26***
	(0.018)	(0.021)	(0.023)	(0.020)
SKY Eligible × Women	-0.011	-0.013	0.0022	-0.017
	(0.029)	(0.032)	(0.036)	(0.032)
p-value: SKY + SKY × women	0.83	0.40	0.31	0.94
Control Mean [non-SKY men]	0	0	0	0
Observations	20526	20488	20488	20488

All indices are calculated following Anderson (2008) and are indexed against the men in non-SKY villages. Individual components of the Information Index in Column (1) are in Table G1. A higher score implies better ability to predict true vs. false correctly. Components of sources of information are in Table G2.
Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parenthesis. Refusals are recoded as missing. Missings due to skip patterns recoded to 0.

This lack of impact could reflect either a null effect of the program or the counterbalancing effects of easier access to both correct and incorrect information. To differentiate between these two hypotheses, the remaining columns of Table 16 ask whether SKY affected how individuals accessed information about Covid-19 and their trust in these information sources. First, we asked respondents if they used different sources to obtain information related to Covid-19. These include institutional (healthcare workers, government officials), traditional (word-of-mouth, television, newspapers), and digital (social media applications) sources. Columns 2-4 present the results of standardized indices, which aggregate use of sources in these categories.

We see that women used all types of news sources less than men. Compared to men in the control group, women are 0.088 standard deviation units less likely to use institutional sources. This gap is even starker for other sources: Women are 0.16 and 0.26 standard deviation units less likely to use traditional and digital sources respectively.

Table 17 turns to an index of trust, aggregated across the same groups of outlet types. For each news source, we asked individuals to report their trust in that source on a 5-point Likert scale ranging from "complete trust" to "no trust at all". Here, we see that women have lower trust in all sources of information – with a larger gender gap for traditional and digital news (0.34 standard deviation units versus 0.19 standard deviation units for institutional sources). We also see that SKY is associated with a marginally significant increase in trust in traditional news sources among women, though we prefer to interpret this with caution given the general lack of impact on outcomes in this domain.

Table 17: Covid-19 Information Environment, Sources, and Trust

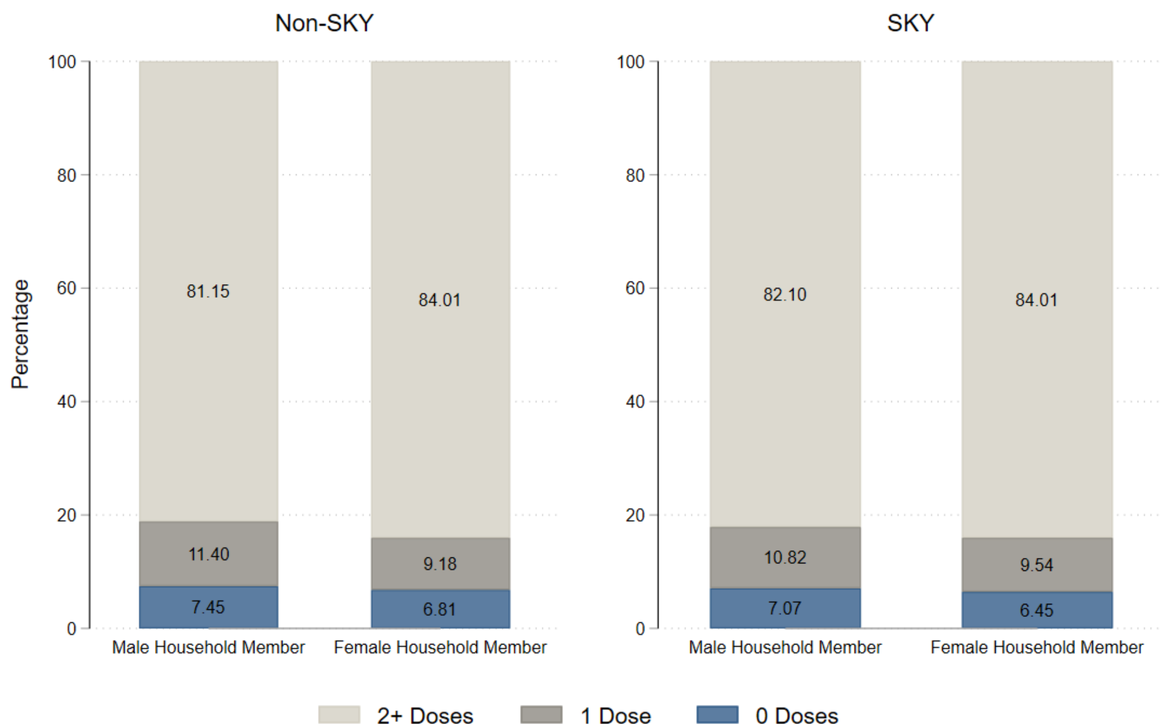
	(1) Institutional News Trust Index	(2) Traditional News Trust Index	(3) Digital News Trust Index
SKY Eligible	-0.025	-0.034	-0.039
	(0.025)	(0.024)	(0.025)
Women	-0.19***	-0.34***	-0.34***
	(0.020)	(0.020)	(0.021)
SKY Eligible × Women	0.042	0.076**	0.012
	(0.030)	(0.031)	(0.034)
p-value: SKY + SKY × women	0.46	0.087	0.30
Control Mean [non-SKY men]	0	0	0
Observations	20554	20551	20552

All indices are calculated following Anderson (2008) and are indexed against the men in non-SKY villages. Trust is measured using a 5-point Likert scale, and a higher score implies higher trust in that source. Components of trust in various sources are in Table G3.

Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parenthesis. Refusals are recoded as missing. Missings due to skip patterns recoded to 0.

Finally, we check whether SKY impacted Covid-19 vaccination status. Our earlier results suggest that the program would be unlikely to affect vaccination through an information channel. However, it still could have made an impact given that owning a smartphone made it easier to register for vaccination following the rollout of India's Aarogya Setu app. During our long-run survey, we collected data on every age-eligible household member's Covid-19 vaccination status. Figure 3 shows that vaccination rates among age-eligible men and women are very similar (and not statistically different) in SKY and non-SKY communities.

Figure 3: Number of Covid-19 Vaccines Received by Household Members



Responses include all household members of vaccine-eligible age in India at the time of survey.

5 Conclusion and Next Steps

We analyze the short- and long-term impacts of SKY, a gender-targeted mobile phone distribution program in Chhattisgarh, India. Our short-term analysis shows that the program was well implemented – most women eligible for a smartphone received one, and as a result gender gaps in phone ownership nearly close and – for smartphone ownership – even reverse. Moreover, both men's and women's attitudes towards women's phone use liberalize. Yet even just weeks following the program, there are some indications that simply giving phones to women is not enough to close digital gender gaps: SKY actually catalyzed relatively *more* experimentation with smart phone tasks among men than women – as a result, gender gaps in smart phone use increased even as the phone ownership gap closed. Consistent with this, after SKY distribution, males are more likely to agree that men have more use for a phone than women do.

Our long-term analysis, which measured impacts on downstream outcomes almost 5 years after phone distribution, when the vast majority of program phones were no longer functional but internet connectivity was still better in SKY areas, finds that SKY had little-to-no lasting impact on average rates of phone use and norms governing phone use. In line with this, we find limited evidence of lasting program impacts on outcomes further down the causal chain, including knowledge and use of digital financial services, local economic activity, and Covid-19 related information and vaccination. We do, however, find some evidence that SKY re-allocated employment across sectors. Implications for economic activities by gender are notable in the context of women's limited economic participation in India and an area we will dive into further in future analysis.

Contextually, it is important to keep in mind that our evaluation spanned a period of rapid smartphone adoption, at least at the household level – by 2023, 84 percent of households in non-SKY communities had at least one smartphone. Yet gender gaps in smartphone ownership remained large, with just 23 percent of surveyed women owning a device. This suggests that when the SKY phone broke, most households did not respond by procuring another phone for the woman. Overall, our results highlight two key challenges facing policymakers who wish to close digital gender gaps by distributing digital assets: First, there is no guarantee that a device transferred to a woman will stay in her hands – especially when pre-existing gender gaps mean that men derive greater actual or perceived utility from the device. Second, one-off transfers are unlikely to have effects that last beyond the lifespan of the asset, especially when perceived or actual returns to women are low. Additional research is needed to identify alternative or complementary programs to address these limitations: for example, building women's digital skills could help reduce gender gaps and build sustained use by increasing women's returns to using a smartphone. Investing in female-centric "use cases" for phones is another way of ensuring women have an economic reason to use the phone. Alternatively, addressing restrictive gender norms governing phone use could unlock more ownership and high-return use among women.

A key caveat is that our analysis thus far has only focused on overall average impacts. SKY may have had more meaningful effects in areas where counterfactual smartphone adoption would have been slower, or 4G networks would not have been built without government intervention. SKY may have also had very different effects for women of differing ages or levels of digital literacy, or in communities with more liberal versus conservative norms. We plan to explore these areas in future analysis to better understand the mechanisms mediating SKY's impact and the potential for phone transfer programs to deliver lasting benefits to marginalized women.

A Appendix: Balance and Descriptive Statistics

Table A1: Balance on Predetermined Characteristics from 2011 Census – Differences in Means (OLS)

	(1) Mean (Ineligible GPs)	(2) Difference (Eligible GPs)	(3) N
Average Household Size	4.450	-0.044	684
	[0.561]	(0.042)	
Fraction Female	0.502	-0.001	684
	[0.013]	(0.001)	
Fraction Scheduled Caste	0.166	0.008	684
	[0.195]	(0.015)	
Fraction Scheduled Tribe	0.317	-0.009	684
	[0.265]	(0.020)	
Has Village Unconnected to Tarmac Road	0.523	-0.025	684
	[0.500]	(0.039)	
Area in Hectares Per Household	1.923	-0.043	684
	[1.013]	(0.087)	
Area Sown (Hectares) Per Household	1.174	-0.074**	684
	[0.425]	(0.030)	
Number Primary Schools Per 1,000 Households	7.261	-0.471***	684
	[2.496]	(0.182)	
Number Middle Schools Per 1,000 Households	2.998	-0.068	684
	[2.112]	(0.150)	
Has Mobile Coverage	0.813	-0.030	684
	[0.390]	(0.031)	
Has Post Office	0.108	0.029	684
	[0.311]	(0.026)	
Has Bus Service	0.585	0.000	684
	[0.493]	(0.038)	
Has Self Help Groups	0.948	0.005	684
	[0.221]	(0.017)	
Has Bank or Co-Op	0.042	-0.002	684
	[0.200]	(0.015)	
Has Fair Price Shop	0.747	0.047	684
	[0.435]	(0.033)	
Left Wing Extremism Affected	0.428	-0.038	684
	[0.495]	(0.038)	

All data from 2011 Indian Census. Standard deviations in square brackets, heteroskedasticity robust standard errors in parentheses. Column 1 reports the mean and standard deviation of the variable below the SKY eligibility threshold. Column 2 reports differences in outcomes above the threshold, with heteroskedasticity robust standard errors in parentheses. Column 3 reports the total sample size.

Table A2: Respondent Characteristics from the Long-Run and Short-Run Studies

	Women		Men	
	Long-Run Study Mean	Short-Run Study Difference	Long-Run Study Mean	Short-Run Study Difference
	(1)	(2)	(3)	(4)
Age	32.908	1.138***	34.236	4.220***
	[6.990]	(0.148)	[9.115]	(0.177)
% Married	0.884	0.116***	0.828	0.172***
	[0.321]	(0.003)	[0.377]	(0.004)
Years of schooling	5.858	-1.040***	7.912	-1.444***
	[4.335]	(0.101)	[3.673]	(0.097)
% Hindu	0.917	-	0.939	0.054***
	[0.275]	(-)	[0.238]	(0.003)
% Scheduled Tribe	0.316	-0.276***	0.312	-0.272***
	[0.465]	(0.007)	[0.463]	(0.007)
% Scheduled Caste	0.157	0.106***	0.157	0.105***
	[0.364]	(0.011)	[0.364]	(0.011)
HH owns land	-	-	0.642	-0.204***
	[-]	(-)	[0.479]	(0.013)
Observations	10282	1696	10277	1696

Standard Deviation reported in square brackets and robust standard errors in parentheses. Refusals and don't knows are missing. Columns (1) and (3) are responses from the long-run study conducted in 13 districts from Section 4. Columns (2) and (4) show the difference between the short-run study district of Raipur (from Section 3) and long-run districts.
***$p \leq 0.01$, **$p \leq 0.05$, *$p \leq 0.10$

Table A3: Respondent Characteristics from the Demographic and Health Survey (DHS, 2019-2021)

	Women			Men		
	Long-Run Study Mean	Short-Run Study Difference	Non-Study Difference	Long-Run Study Mean	Short-Run Study Difference	Non-Study Difference
	(1)	(2)	(3)	(4)	(5)	(6)
Age	30.062	0.612**	0.033	33.273	0.249	0.397
	[8.042]	(0.303)	(0.108)	[10.265]	(1.158)	(0.331)
% Married	0.756	0.027	-0.028***	0.709	-0.056	-0.004
	[0.430]	(0.023)	(0.007)	[0.455]	(0.051)	(0.018)
Years of schooling	6.572	0.555*	-1.102***	7.740	0.623**	-1.166***
	[4.506]	(0.283)	(0.137)	[3.894]	(0.308)	(0.230)
% Hindu	0.987	0.010***	-0.016***	0.984	0.016**	-0.015
	[0.114]	(0.003)	(0.005)	[0.124]	(0.006)	(0.011)
% Scheduled Tribe	0.283	-0.249***	0.376***	0.268	-0.224***	0.327***
	[0.451]	(0.020)	(0.021)	[0.443]	(0.038)	(0.039)
% Scheduled Caste	0.158	0.113*	-0.088***	0.147	0.015	-0.027
	[0.365]	(0.066)	(0.012)	[0.354]	(0.074)	(0.026)
HH owns land	0.646	-0.136***	0.098***	0.650	-0.042	0.103***
	[0.478]	(0.036)	(0.013)	[0.477]	(0.077)	(0.028)
% Owns a Mobile Phone	0.353	0.068	0.010	0.872	0.027	-0.140***
	[0.478]	(0.065)	(0.025)	[0.334]	(0.038)	(0.020)
% Used Internet	0.200	0.081	0.027	0.470	0.182**	-0.073***
	[0.400]	(0.086)	(0.021)	[0.499]	(0.077)	(0.025)
% Has a Bank Account	0.829	0.049*	-0.038	0.850	0.005	-0.067***
	[0.377]	(0.028)	(0.023)	[0.357]	(0.048)	(0.024)
Observations	8936	378	9534	1482	69	1494

Standard Deviation reported in square brackets and standard errors clustered at the DHS Primary Sampling Unit in parentheses. All data from the DHS (2019-2021), also known as NFHS-5. Sample restricted to rural areas and to women aged 18-45 and men aged 18-54. Columns (1) and (4) are responses to the DHS survey from the 13 districts in the long-run study from Section 4. Columns (2) and (5) show the difference between the short-run study district of Raipur (from Section 3) and long-run districts. Columns (3) and (6) show the difference between the non-study (excluding Raipur) and long-run districts.
***$p \leq 0.01$, **$p \leq 0.05$, *$p \leq 0.10$

B Appendix: First Stage

Table B1: Impact of SKY on Women's Phone Ownership and Access

	(1) Respondent Uses Own Phone	(2) Respondent Is Primary User of the Phone	(3) Respondent Doesn't Need Permission to Use Phone	(4) Respondent Uses Phone Outside the House
SKY Eligible	0.0026	-0.0064	0.011	-0.00096
	(0.0093)	(0.0092)	(0.011)	(0.012)
Control Mean [non-SKY]	0.23	0.24	0.67	0.53
Observations	10258	10266	10282	10281

This table shows the components of the Phone Access Index in Table 8.
Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parentheses. Refusals are recoded as missing. Missings due to skip patterns recoded to 0.

Table B2: Respondent Has Done the Following Basic Phone Activities in the Past Month

	(1) Dialed Numbers	(2) Picked Up Calls	(3) Sent SMS
SKY Eligible	-0.014	-0.0095	-0.0020
	(0.0094)	(0.0091)	(0.0088)
Women	-0.29***	-0.16***	-0.14***
	(0.0084)	(0.0082)	(0.0067)
SKY Eligible × Women	0.012	0.0048	-0.0083
	(0.013)	(0.013)	(0.011)
p-value: SKY + SKY × women	0.86	0.69	0.12
Control Mean [non-SKY men]	0.82	0.84	0.25
Observations	20543	20543	20543

This table shows the components of the phone use index in Table 8.
Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parentheses. Refusals are recoded as missing. Missings due to skip patterns recoded to 0.

Table B3: Respondent Has Done the Following Smart Phone Activities in the Past Month

	(1) Use WhatsApp	(2) Used Facebook	(3) Used YouTube	(4) Took a Photo	(5) Played a Video	(6) Ran an Internet Search	(7) Read Information Online
SKY Eligible	0.0051	-0.0056	0.0090	0.0078	0.0029	0.019*	0.010
	(0.011)	(0.010)	(0.011)	(0.011)	(0.011)	(0.0099)	(0.0096)
Women	-0.28***	-0.24***	-0.31***	-0.24***	-0.27***	-0.21***	-0.20***
	(0.0084)	(0.0069)	(0.0092)	(0.0084)	(0.0085)	(0.0076)	(0.0072)
SKY Eligible × Women	-0.0092	0.0051	-0.019	-0.018	0.0029	-0.027**	-0.021*
	(0.013)	(0.011)	(0.014)	(0.013)	(0.014)	(0.011)	(0.011)
p-value: SKY + SKY × women	0.65	0.93	0.30	0.28	0.57	0.24	0.11
Control Mean [non-SKY men]	0.49	0.30	0.57	0.49	0.55	0.33	0.30
Observations	20546	20545	20545	20544	20544	20545	20545

This table shows the components of the phone use index in Table 8.
Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parentheses. Refusals are recoded as missing. Missings due to skip patterns recoded to 0.

Table B4: Impact of SKY on non-JIO internet speeds

	Non-Reliance JIO	
	(1) Avg. download speed	(2) Avg. upload speed
SKY Eligible	0.55	0.48
	(0.78)	(0.55)
Control Mean [non-SKY]	8.15	3.19
Observations	634	634

Results from a GP-level regression displayed. Outcomes in columns (1)-(2) denote the average upload and download speeds across all *but* Reliance JIO service providers (Airtel, Idea, and others). Excluding Reliance JIO speed tests reduced the coverage of GPs since our enumerators relied on Reliance JIO to conduct at least one speed test in the GP. Upload and download speeds are in Mbps.

C Appendix: Robustness Checks on Short-term Results

Table C1: Short-Term Impacts of SKY on Phone Ownership

	Any phone ownership			Smartphone ownership		
	Household	Men	Women	Household	Men	Women
	(1)	(2)	(3)	(4)	(5)	(6)
Post	0.085***	0.101**	0.513***	0.496***	0.166***	0.606***
	(0.021)	(0.045)	(0.055)	(0.045)	(0.047)	(0.059)
Pre-Dist Mean	0.939	0.764	0.236	0.440	0.209	0.048
N	1696	1696	1696	1696	1696	1696
Baseline Controls	Yes	Yes	Yes	Yes	Yes	Yes

Specification includes replacement sample, block and female literacy fixed effects. Standard errors clustered at the village level and reported in parentheses. Baseline demographics added as additional control for robustness check.

Table C2: Short-Term Impacts of SKY on Phone Use

	Basic tasks index	Smart tasks index
	(1)	(2)
Post	0.156**	0.272***
	(0.075)	(0.062)
Women	-0.425***	-0.390***
	(0.035)	(0.031)
Post x Women	-0.032	-0.157***
	(0.050)	(0.048)
p-value: Post + (Post x Women) = 0	0.055	0.040
Pre-Dist Mean [Men]	0.000	0.000
N	3389	3385
Baseline Controls	Yes	Yes

Outcomes in columns (1) and (2) are standardized indices of basic and smart phone tasks. All indices created following Anderson (2008) and indexed against the men in the pre-distribution villages. Specification includes replacement sample, block and female literacy fixed effects. Standard errors clustered at the village level and reported in parentheses. Baseline demographics added as additional control for robustness check.

Table C3: Short-Term Impacts of SKY on First Order Beliefs Around Women's Phone Use

	___ thinks it is appropriate for ___ to use phone:		
	Respondent; Unmarried women	Respondent; Married women	Disagrees that men have more uses for a phone
	(1)	(2)	(3)
Post	-0.014	-0.000	-0.140***
	(0.031)	(0.041)	(0.041)
Women	-0.027*	0.029	0.043*
	(0.015)	(0.022)	(0.023)
Post x Women	0.006	0.006	0.114***
	(0.024)	(0.030)	(0.033)
p-value: Post + (Post x Women) = 0	0.815	0.892	0.550
Pre-Dist Mean [Men]	0.156	0.222	0.313
N	3358	3355	3357
Baseline Controls	Yes	Yes	Yes

Specification includes replacement sample, block and female literacy fixed effects. Standard errors clustered at the village level and reported in parentheses. Baseline demographics added as additional control for robustness check.

Table C4: Short-Term Impacts of SKY on Second Order Beliefs Around Women's Phone Use

	The number of _____ that think it is appropriate for _____ to use phone:			
	Village women; Unmarried women	Village women; Married women	Village men; Unmarried women	Village men; Married women
	(1)	(2)	(3)	(4)
Post	0.380	0.279	0.063	0.139
	(0.231)	(0.247)	(0.218)	(0.240)
Women	0.613***	0.725***	0.258**	0.280*
	(0.144)	(0.141)	(0.131)	(0.145)
Post x Women	-0.744***	-0.497***	-0.481***	-0.458**
	(0.191)	(0.190)	(0.170)	(0.191)
p-value: Post + (Post x Women) = 0	0.107	0.380	0.040	0.165
Pre-Dist Mean [Men]	3.423	3.825	3.390	3.846
N	3304	3291	3297	3294
Baseline Controls	Yes	Yes	Yes	Yes

Specification includes replacement sample, block and female literacy fixed effects. Standard errors clustered at the village level and reported in parentheses. Baseline demographics added as additional control for robustness check.

D Appendix: Community-level Outcomes

Table D1: Impact of SKY on number of local businesses

	(1) Pvt Grocery	(2) Public Grocery	(3) Tailoring	(4) Clothing	(5) Mills/Kilns	(6) Small Mfg	(7) Eateries	(8) Phone Recharge	(9) Medical	(10) Other biz
SKY Eligible	0.45**	0.044	0.014	0.045	-0.076	-0.00015	-0.029	0.052	-0.0081	-0.010
	(0.20)	(0.038)	(0.13)	(0.060)	(0.059)	(0.012)	(0.054)	(0.059)	(0.040)	(0.050)
Control Mean [non-SKY]	5.48	0.97	1.39	0.43	0.50	0.034	0.36	0.58	0.22	0.32
Observations	1406	1410	1398	1408	1410	1409	1410	1410	1410	1413

Outcomes displayed are counts of kinds of businesses in the village of the ward member surveyed and winsorized at the 99th percentile. Refusals are missing. Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parentheses.

Table D2: Impact of SKY on labor market tightness for men

	Ease of finding jobs for **men** in:				
	(1) Ag work (sowing) in kharif	(2) Ag work (harvesting) in kharif	(3) Ag work before kharif	(4) Casual labor in kharif	(5) Casual labor before kharif
SKY Eligible	0.080	-0.10	-0.048	0.15	-0.17
	(0.15)	(0.16)	(0.20)	(0.19)	(0.18)
Control Mean [non-SKY]	7.88	7.58	5.50	5.43	5.59
Observations	1399	1397	1392	1388	1378

A higher value of the outcome represents tighter labor markets where jobs are easily available (higher vacancies) for workers looking. Refusals are missing. Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parentheses.

Table D3: Impact of SKY on labor market tightness for women

	Ease of finding jobs for **women** in:				
	(1) Ag work (sowing) in kharif	(2) Ag work (harvesting) in kharif	(3) Ag work before kharif	(4) Casual labor in kharif	(5) Casual labor before kharif
SKY Eligible	0.24*	0.039	-0.033	0.11	-0.083
	(0.13)	(0.17)	(0.21)	(0.19)	(0.19)
Control Mean [non-SKY]	8.25	7.61	5.52	5.14	5.25
Observations	1401	1399	1397	1385	1378

A higher value of the outcome represents tighter labor markets where jobs are easily available for workers looking. Refusals are missing. Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parentheses.

Table D4: Impact of SKY on price dispersion: Spread

	Max-min spread (INR/kg) in the prices of :							
	(1) Rice	(2) Sugar	(3) Lentil	(4) Tomato	(5) Onion	(6) Eggplant	(7) Potatoes	(8) Chillies
SKY eligible	0.45	0.60	0.79	-0.33	0.87	0.099	0.12	1.78
	(0.69)	(0.69)	(1.80)	(1.61)	(0.70)	(0.55)	(0.53)	(3.30)
Control Mean [non-SKY]	16.7	14.4	68.6	31.6	24.0	23.4	16.7	89.9
Observations	684	684	684	684	684	684	684	684

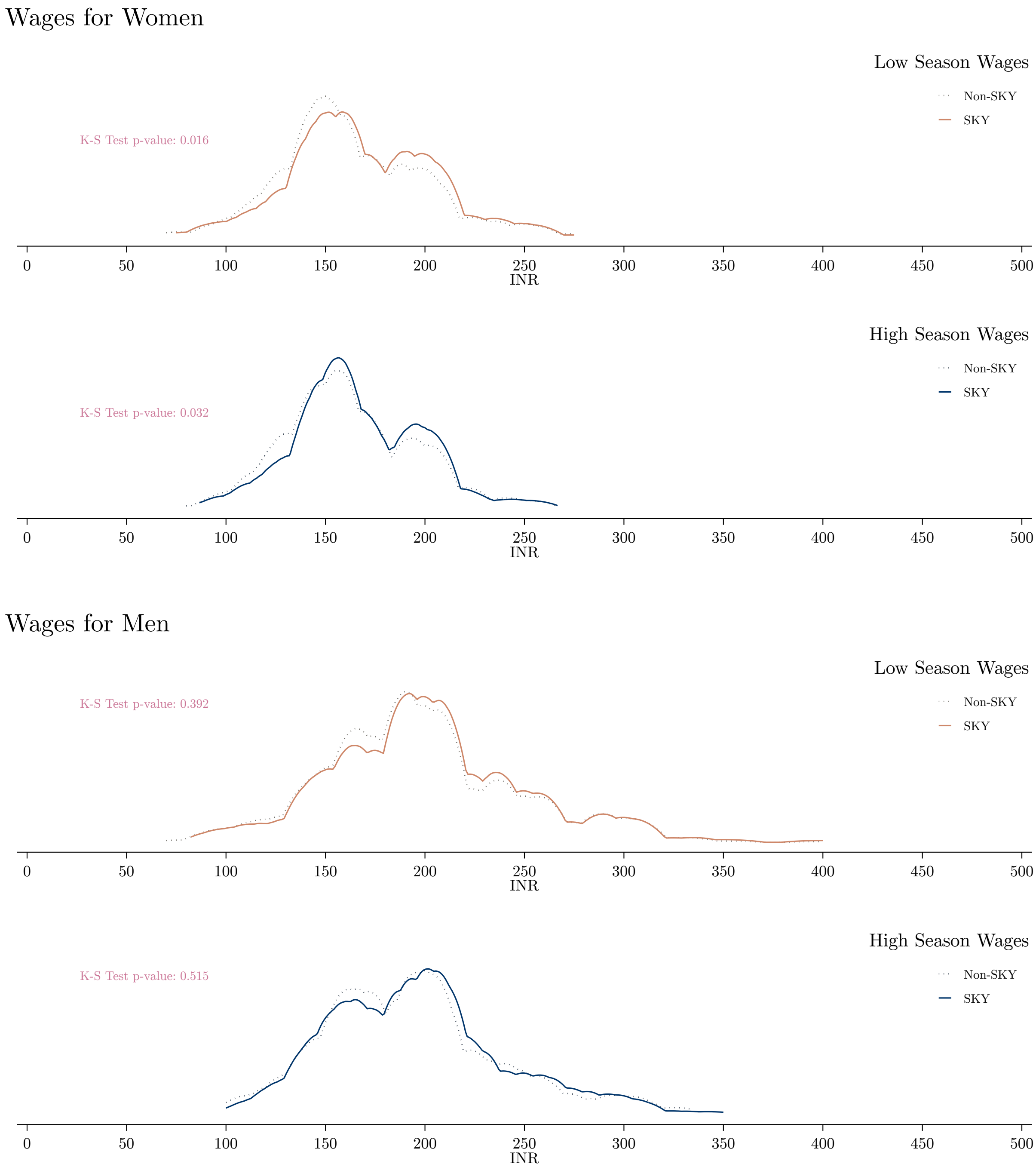
Table above reports the effect of SKY on the spread of prices for each item. Data points with zero prices were set to missing and the distribution was winsorized at the 99th percentile. Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parentheses.

Table D5: Impact of SKY on price dispersion: Inter-quartile Range (IQR)

	Inter-quartile range (INR/kg) in the prices of :							
	(1) Rice	(2) Sugar	(3) Lentil	(4) Tomato	(5) Onion	(6) Eggplant	(7) Potatoes	(8) Chillies
SKY eligible	-0.14	-0.48***	-1.19	0.29	0.18	-0.80*	0.064	-2.15*
	(0.24)	(0.18)	(0.96)	(0.60)	(0.37)	(0.43)	(0.26)	(1.28)
Control Mean [non-SKY]	4.07	1.63	24.2	9.31	6.06	9.39	4.13	31.7
Observations	684	684	684	684	684	684	684	684

Table above reports the effect of SKY on the inter-quartile range of prices for each item. Data points with zero prices were set to missing and the distribution was winsorized at the 99th percentile. Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parentheses.

Figure D1: K-Density Plot of Wages



E Appendix: Digital Financial Services

Table E1: Most Common Uses of Digital Financial Services

	(1) Online Payments	(2) Payment at Stores	(3) Transfers to Friends & Family	(4) Bill Payment	(5) Phone Recharge	(6) Receiving Wages	(7) Loan Repayment	(8) Checking Balance
SKY Eligible	0.0022	0.0078	0.0071	0.011	0.012	0.0026	-0.0011	0.00043
	(0.0093)	(0.0095)	(0.0090)	(0.0079)	(0.0094)	(0.0058)	(0.0021)	(0.0014)
Women	-0.20***	-0.20***	-0.18***	-0.12***	-0.19***	-0.069***	-0.0098***	0.0056
	(0.0063)	(0.0064)	(0.0060)	(0.0051)	(0.0061)	(0.0038)	(0.0014)	(0.0048)
SKY Eligible × Women	-0.0059	-0.011	-0.0099	-0.013*	-0.018*	-0.0062	0.0026	0.0031
	(0.0098)	(0.0100)	(0.0096)	(0.0081)	(0.0098)	(0.0060)	(0.0024)	(0.0089)
p-value: SKY + SKY × women	0.30	0.42	0.42	0.40	0.099	0.025	0.17	0.69
Control Mean [non-SKY men]	0.22	0.22	0.20	0.14	0.22	0.075	0.011	0.0010
Observations	20555	20555	20556	20555	20555	20555	20555	3414

Specificatn includes district fixed effects. Standard errors clustered at the GP level and reported in parenthesis. Refusals are recoded as missing. Missings due to skip patterns recoded to 0.

F Appendix: Employment and Income

Table F1: Impact on Information on Income-Generating Activities in the Past 3 Months

	(1) Making or receiving calls	(2) SMS or WhatsApp	(3) Watching vidoes	(4) Using other apps	(5) Web surfing or internet search
SKY Eligible	-0.011	-0.0028	-0.0024	0.0079	-0.00068
	(0.011)	(0.0069)	(0.0075)	(0.0049)	(0.0063)
Women	-0.28***	-0.087***	-0.076***	-0.045***	-0.072***
	(0.0080)	(0.0052)	(0.0059)	(0.0034)	(0.0049)
SKY Eligible × Women	0.0047	-0.0031	-0.0054	-0.0091	-0.00090
	(0.013)	(0.0078)	(0.0090)	(0.0056)	(0.0072)
p-value: SKY + SKY × women	0.29	0.10	0.12	0.59	0.64
Control Mean [non-SKY men]	0.37	0.12	0.13	0.058	0.097
Observations	20557	20557	20557	20557	20557

Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parentheses. Refusals are recoded as missing. Missings due to skip patterns recoded to 0.

Table F2: Impact on Information on Government Schemes in the Past 3 Months

	(1) Making or receiving calls	(2) SMS or WhatsApp	(3) Watching vidoes (e.g. YouTube)	(4) Using other apps	(5) Web surfing or internet search
SKY Eligible	-0.0011	0.0033	0.0038	0.0078	0.0099
	(0.0081)	(0.0056)	(0.0070)	(0.0053)	(0.0077)
Women	-0.11***	-0.050***	-0.080***	-0.048***	-0.11***
	(0.0063)	(0.0040)	(0.0051)	(0.0037)	(0.0054)
SKY Eligible × Women	-0.017*	-0.012**	-0.0084	-0.010*	-0.0095
	(0.0092)	(0.0062)	(0.0078)	(0.0059)	(0.0085)
p-value: SKY + SKY × women	0.00022	0.0030	0.27	0.26	0.92
Control Mean [non-SKY men]	0.17	0.076	0.12	0.063	0.14
Observations	20556	20556	20556	20556	20556

Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parentheses. Refusals are recoded as missing. Missings due to skip patterns recoded to 0.

Table F3: Impact on Paid Work Done in the Past Year

	(1) Agriculture Labor on Own Land	(2) Animal Husbandry	(3) Small Business or Self Employment	(4) Casual Agriculture Labor	(5) Casual Non Agriculture Labor	(6) NREGA Work	(7) Salaried Employment
SKY Eligible	-0.000037	0.015**	-0.0069	-0.0042	-0.0038	-0.0061	0.013*
	(0.012)	(0.0061)	(0.0084)	(0.012)	(0.011)	(0.016)	(0.0078)
Women	-0.097***	0.024***	0.0016	0.080***	-0.19***	-0.0024	-0.040***
	(0.0073)	(0.0051)	(0.0068)	(0.0095)	(0.0084)	(0.0099)	(0.0059)
SKY Eligible × Women	-0.0022	-0.024***	-0.021*	0.0024	-0.0057	-0.013	-0.010
	(0.012)	(0.0076)	(0.011)	(0.015)	(0.013)	(0.017)	(0.0094)
p-value: SKY + SKY × women	0.86	0.19	0.0045	0.87	0.24	0.19	0.63
Control Mean [non-SKY men]	0.67	0.067	0.17	0.41	0.33	0.44	0.10
Observations	20558	20558	20556	20557	20557	20554	20554

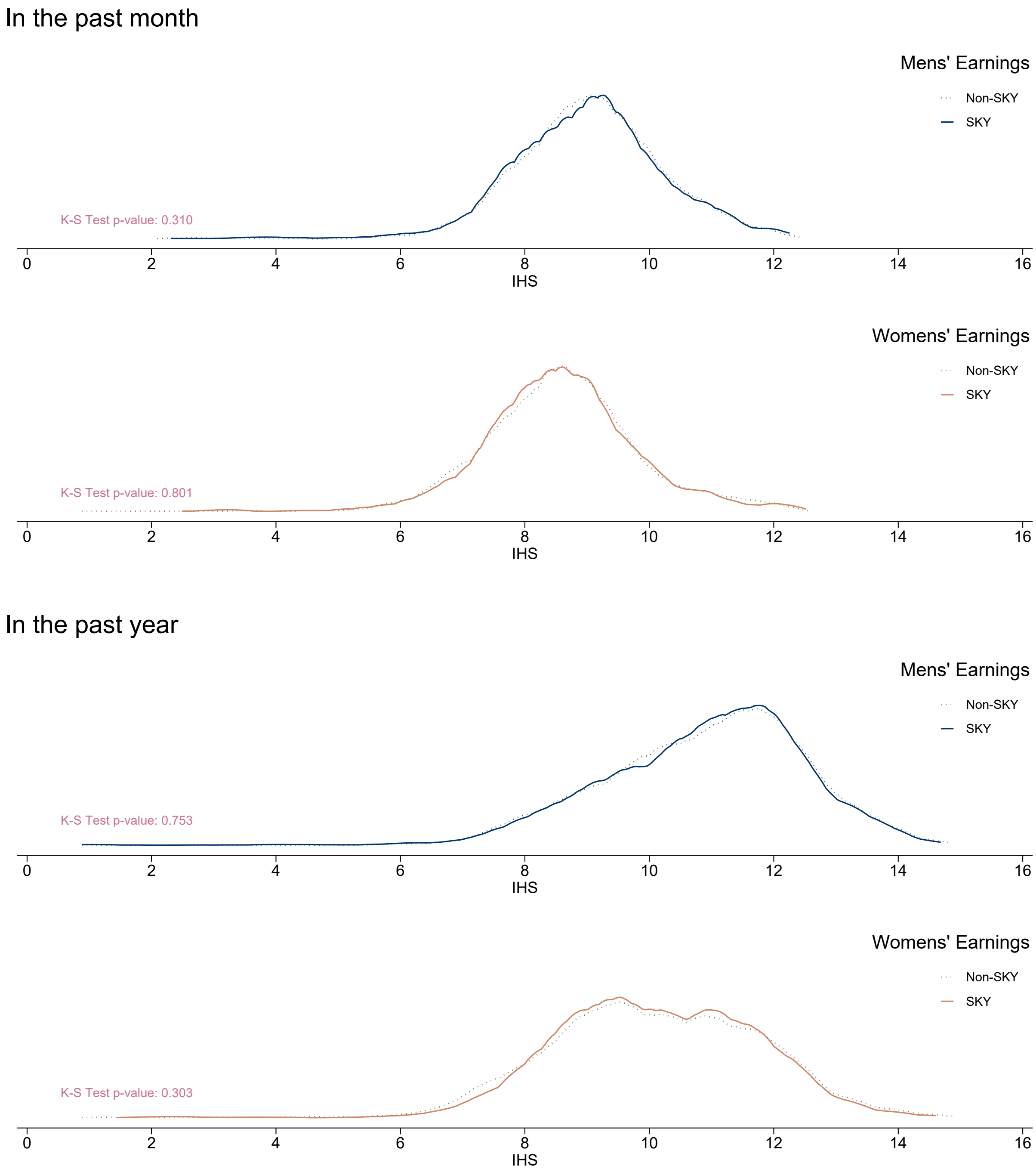
Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parentheses. Refusals are recoded as missing. Missings due to skip patterns recoded to 0.

Table F4: Impact on Paid Work Done in the Past Month

	(1) Agriculture Labor on Own Land	(2) Animal Husbandry	(3) Small Business or Self Employment	(4) Casual Agriculture Labor	(5) Casual Non Agriculture Labor	(6) NREGA Work	(7) Salaried Employment
SKY Eligible	-0.011	0.010*	-0.0092	0.0054	-0.0033	-0.011	0.014**
	(0.013)	(0.0054)	(0.0075)	(0.0080)	(0.0090)	(0.013)	(0.0068)
Women	-0.056***	0.018***	-0.0080	0.041***	-0.11***	0.020**	-0.026***
	(0.0077)	(0.0047)	(0.0058)	(0.0068)	(0.0062)	(0.0084)	(0.0051)
SKY Eligible × Women	-0.00051	-0.017**	-0.017*	0.0062	-0.0063	-0.011	-0.011
	(0.012)	(0.0068)	(0.0094)	(0.011)	(0.0100)	(0.013)	(0.0083)
p-value: SKY + SKY × women	0.32	0.26	0.0018	0.25	0.080	0.082	0.45
Control Mean [non-SKY men]	0.29	0.053	0.14	0.12	0.18	0.23	0.075
Observations	20558	20558	20556	20555	20557	20553	20554

Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parentheses. Refusals are recoded as missing. Missings due to skip patterns recoded to 0.

Figure F1: K-Density Plot of Earnings



Notes: Density plots for men and womens' earnings (inclusive of profits) are plotted across varying reference periods. The distribution plotted is an Inverse Hyperbolic Sine (IHS) transformation of the winsorized (1st and 99th percentile) earnings (INR) distribution. We show the *intensive margin*, which is the distribution of earnings conditional on non-zero earnings. P-values for the Kolmogorov-Smirnov (K-S) test that tests for the equality of plotted distributions (the intensive margin) across SKY and non-SKY are reported.

G Appendix: Covid-19 Information Environment

Table G1: Summary of Responses to Information Questions

	(1) Mobile phone towers are leading to the spread of covid	(2) Smelling camphor, cloves, ajwain helps prevent covid	(3) Eating plenty of garlic can help cure a coronavirus infection	(4) Drinking cow urine helps prevent covid	(5) People who have diabetes are more at risk for covid	(6) Losing one's sense of taste is a symptom of Covid	(7) Vaccines have been developed that are effective against covid	(8) Mean Likert Score (1-5)
SKY Eligible	0.0057	-0.038	-0.017	-0.043	0.0034	0.029	0.046*	-0.0028
	(0.031)	(0.033)	(0.031)	(0.038)	(0.033)	(0.032)	(0.024)	(0.014)
Women	-0.38***	-0.41***	-0.36***	-0.35***	0.23***	0.15***	0.051**	-0.15***
	(0.025)	(0.027)	(0.027)	(0.028)	(0.027)	(0.027)	(0.021)	(0.011)
SKY Eligible × Women	-0.012	0.044	0.021	0.022	-0.018	-0.038	-0.036	-0.0011
	(0.043)	(0.042)	(0.042)	(0.043)	(0.043)	(0.042)	(0.032)	(0.018)
p-value: SKY + SKY × women	0.87	0.87	0.89	0.57	0.63	0.78	0.67	0.80
Control Mean [non-SKY men]	4.12	2.99	2.77	3.03	3.61	3.72	4.32	3.51
Observations	20317	20160	20204	20162	20297	20256	20374	20526

Columns (1)-(4) are fake statements and (5)-(7) are true. A higher score implies better ability to correctly predict true vs. false. Column (8) is the mean of the 5-point Likert scale of correct beliefs. Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parenthesis. Refusals are recoded as missing. Missings due to skip patterns recoded to 0.

Table G2: Sources of Covid-Related Information

	Institutional		Traditional			Digital		
	(1) Health workers	(2) Government officials	(3) Family or Friends	(4) Newspapers	(5) TV	(6) WhatsApp	(7) Facebook	(8) YouTube
SKY Eligible	0.012*	0.0065	0.0086	0.0088	0.0049	0.011	0.0023	0.0087
	(0.0070)	(0.0093)	(0.0084)	(0.010)	(0.0082)	(0.011)	(0.011)	(0.011)
Women	0.0048	-0.071***	-0.0077	-0.13***	-0.041***	-0.096***	-0.10***	-0.15***
	(0.0063)	(0.0081)	(0.0076)	(0.0094)	(0.0070)	(0.0097)	(0.0093)	(0.010)
SKY Eligible × Women	-0.011	0.0077	-0.00069	0.0064	-0.0016	-0.0081	0.00036	-0.019
	(0.0096)	(0.013)	(0.012)	(0.015)	(0.011)	(0.016)	(0.015)	(0.016)
p-value: SKY + SKY × women	0.92	0.18	0.38	0.23	0.73	0.84	0.82	0.41
Control Mean [non-SKY men]	0.89	0.83	0.87	0.75	0.86	0.62	0.45	0.61
Observations	20488	20488	20488	20488	20488	20488	20488	20488

Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parenthesis. Refusals are recoded as missing. Missings due to skip patterns recoded to 0.

Table G3: Trust in Different Sources of Information

	Institutional		Traditional			Digital		
	(1) Health workers	(2) Government officials	(3) Family or Friends	(4) Newspapers	(5) TV	(6) WhatsApp	(7) Facebook	(8) YouTube
SKY Eligible	-0.022	-0.029	-0.0063	-0.041	-0.054**	-0.031	-0.037	-0.043*
	(0.028)	(0.029)	(0.026)	(0.028)	(0.026)	(0.028)	(0.027)	(0.024)
Women	-0.19***	-0.21***	-0.24***	-0.38***	-0.35***	-0.35***	-0.27***	-0.36***
	(0.024)	(0.023)	(0.023)	(0.024)	(0.022)	(0.024)	(0.022)	(0.022)
SKY Eligible × Women	0.062*	0.026	0.057	0.084**	0.070**	-0.000085	0.022	0.011
	(0.035)	(0.035)	(0.036)	(0.037)	(0.034)	(0.038)	(0.036)	(0.035)
p-value: SKY + SKY × women	0.14	0.91	0.065	0.11	0.54	0.28	0.56	0.24
Control Mean [non-SKY men]	3.65	3.48	3.70	3.49	3.50	2.91	2.48	2.79
Observations	20549	20547	20548	20546	20543	20550	20549	20547

A higher score implies higher trust in that source and trust is measured using a 5-point Likert scale.
Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parenthesis. Refusals are recoded as missing. Missings due to skip patterns recoded to 0.

Table G4: Sources of General Information

	Institutional		Traditional			Digital		
	(1) Health workers	(2) Government officials	(3) Family or Friends	(4) Newspapers	(5) TV	(6) WhatsApp	(7) Facebook	(8) YouTube
SKY Eligible	0.023	0.00095	0.0040	0.00028	-0.036	0.015	-0.018	0.027
	(0.023)	(0.024)	(0.034)	(0.039)	(0.040)	(0.036)	(0.029)	(0.035)
Women	-0.087***	-0.23***	-0.42***	-0.61***	-0.59***	-0.69***	-0.44***	-0.78***
	(0.019)	(0.019)	(0.028)	(0.028)	(0.032)	(0.025)	(0.021)	(0.026)
SKY Eligible × Women	-0.018	0.0030	0.023	0.015	-0.0018	-0.040	0.00067	-0.086*
	(0.028)	(0.028)	(0.045)	(0.043)	(0.046)	(0.041)	(0.034)	(0.044)
p-value: SKY + SKY × women	0.81	0.85	0.41	0.55	0.28	0.36	0.32	0.049
Control Mean [non-SKY men]	1.55	1.60	2.38	2.08	2.62	2.26	1.67	2.43
Observations	20250	20268	20379	20254	20310	20000	19873	19879

The table lists sources of consumption for general news. A higher score implies more frequent use of that source as measured using a 5-point Likert scale.
Specification includes district fixed effects. Standard errors clustered at the GP level and reported in parenthesis. Refusals are recoded as missing. Missings due to skip patterns recoded to 0.

H Appendix: Outcome Variable Construction - Short Run Effects

H.1 Phone Ownership

- *Any Phone Ownership* - Phone ownership information is extracted from the phone roster that asks the respondent(s) to list all the phones in the household and asks who owns each phone. For household phone ownership, we take the union of the husband and wife responses.
- *Smartphone Ownership* - Smartphone ownership information is extracted in a similar way to any phone ownership but only counting smartphones owned by respondents and households.

H.2 Phone Use

- *Percent Basic Phone Tasks Performed* - The survey question is "In the past month how often have you done this activity?" We consider the responses "daily" and "few times in a week" as recent use. Basic uses include dialing calls, receiving calls, and sending/receiving SMS's. The outcome variable is then calculated by taking an average of the responses for the basic tasks questions.
- *Percent Advanced Phone Tasks Performed* - The survey question is "In the past month how often have you done this activity?" We consider the responses "daily" and "few times in a week" as recent use.Advanced uses include using WhatsApp, taking photos, taking video, and using mobile internet. The outcome variable is then calculated by taking an average of the responses for the basic tasks questions.

H.3 Norms Governing Phone Use

- *Percent of Time Agrees Married/Unmarried Women Can Use Phones* - This variable construction is based on the survey questions "In your opinion, do you think it is appropriate for married/unmarried women to own their own phone and use it under/without their family's supervision?". The response "Almost always inappropriate" is coded as 0. Then, we take an average to compute the percent of time respondents agree that women can use phones.
- *Agrees Men Have More Use for Phones Than Women Do* - The variable construction is based on the survey question "Men have more uses for a phone than women do." The response "Agree" is coded as 1. "Neutral" and "Disagree" is coded as 0.

References

Adema, J., C. G. Aksoy, and P. Poutvaara (2022). Mobile internet access and the desire to emigrate. Technical report, CESifo Working Paper Number 9758.

Aker, J. C. and M. Fafchamps (2015, 10). Mobile Phone Coverage and Producer Markets: Evidence from West Africa. *The World Bank Economic Review 29*(2), 262–292.

Aker, J. C., C. Ksoll, and T. J. Lybbert (2012). Can Mobile Phones Improve Learning? Evidence from a Field Experiment in Niger. *American Economic Journal: Applied Economics 4*(4), 94–120.

Anderson, M. L. (2008). Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects. *Journal of the American statistical Association 103*(484).

Banu, A. (2016). Human Development, Disparity and Vulnerability: Women in South Asia. *UNDP (United Nations Development Programme)*.

Barboni, G., A. Bhattacharya, E. Field, R. Pande, N. Rigol, S. Schaner, A. Shukla, and C. Troyer Moore (2023). A Tough Call: Understanding the Impact of Mobile Technology on Women's Work, Gender Gaps, Social Norms, and Misinformation. Pre-analysis plan.

Barboni, G., E. Field, R. Pande, N. Rigol, S. Schaner, and C. Troyer Moore (2018). A tough call: Understanding barriers to and impacts of women's mobile phone adoption in india.

Barboni, G., E. Field, R. Pande, S. Schaner, and C. Troyer Moore (2019). The Short-Run Impacts of a Mass Smartphone Distribution to Women: Results from the Mor Awaaz Baseline Survey.

Bernhardt, A., E. Field, R. Pande, and N. Rigol (2019, September). Household matters: Revisiting the returns to capital among female microentrepreneurs. *American Economic Review: Insights 1*(2), 141–60.

Cattaneo, M. D., N. Idrobo, and R. Titiunik (2019). *A practical introduction to regression discontinuity designs: Foundations*. Cambridge University Press.

Cattaneo, M. D., N. Idrobo, and R. Titiunik (2023). A practical introduction to regression discontinuity designs: Extensions. *arXiv preprint arXiv:2301.08958*.

Chiplunkar, G. and P. K. Goldberg (2022a, December). The employment effects of mobile internet in developing countries. Working Paper 30741, National Bureau of Economic Research.

Chiplunkar, G. and P. K. Goldberg (2022b, December). The employment effects of mobile internet in developing countries. Working Paper 30741, National Bureau of Economic Research.

Dammert, A. C., J. Galdo, and V. Galdo (2015, Jul). Integrating Mobile Phone Technologies into Labor-Market Intermediation: A Multi-Treatment Experimental Design. *IZA Journal of Labor & Development 4*(1), 11.

Dammert, A. C., J. C. Galdo, and V. Galdo (2014). Preventing dengue through mobile phones: evidence from a field experiment in peru. *Journal of Health Economics 35*, 147–161.

GSMA (2019). Connected women: The mobile gender gap report 2019. Technical report.

GSMA (2022). Connected women: The mobile gender gap report 2022. Technical report.

Guriev, S., N. Melnikov, and E. Zhuravskaya (2019, 01). 3g internet and confidence in government. *SSRN Electronic Journal*.

Hjort, J. and J. Poulsen (2019, March). The arrival of fast internet and employment in africa. *American Economic Review 109*(3), 1032–79.

Ho, L., S. Jalota, and A. Karandikar (2024). Bringing work home: Flexible arrangements as gateway jobs for women in west bengal.

Jalota, S. and L. Ho (2024). What works for her? how work-from-home jobs affect female labor force participation in urban india.

Jayachandran, S. (2021). Social norms as a barrier to women's employment in developing countries. *IMF Economic Review 69*(3), 576–595.

Jensen, R. (2007). The digital provide: Information (technology), market performance, and welfare in the south indian fisheries sector. *Quarterly Journal of Economics 122*, 879–924.

Manacorda, M. and A. Tesei (2020). Liberation technology: Mobile phones and political mobilization in africa. *Econometrica 88*(2), 533–567.

Pew Research Center (2019). Smartphone ownership is growing rapidly around the world, but not always equally.

RBI (2019). Handbook of Statistics on Indian States 2018-19. Technical report, Reserve Bank of India.

Suri, T. and W. Jack (2016). The long-run poverty and gender impacts of mobile money. *Science 354*(6317), 1288–1292.