What Works For Her?

How Work-from-Home Jobs Affect Female Labor Force Participation in Urban India*

Suhani Jalota† Lisa Ho
(Job Market Paper)

January 20, 2024

(Click here for the most recent version, updated frequently)

Abstract

In many developing countries, married women face significant barriers to entering the workforce, that are often rooted in gender norms. These may manifest as *practical constraints*—like travel restrictions and housework responsibilities—and other less tangible *domesticity constraints*—the expectation that a woman's role is confined at home. We design an experiment to distinguish between these barriers by establishing new job offices for part-time, smartphone-based digital work with minimal practical constraints: the office is local, located within a five-minute walk from home, only for women, and permits children. We assigned 3,200 wives in Mumbai to the same jobs, either from home or from the office, and cross-randomized them to one of three monthly wage levels (low, medium, or high). We find that 56% of wives started working from home, while only 27% took up office jobs, matching India's female labor force participation rate. Even wages that double household income did not significantly affect job uptake. A parallel experiment revealed husbands were more responsive to wages and indifferent to job location for themselves, yet over half were opposed to their wives working outside the home. A follow-up experiment found that enforcing a two-minute office check-in daily to a home-based job, making a woman's work status visible outside, significantly reduced job take-up, especially among women from less progressive households. Taken together, the experiments suggest that even beyond practical constraints, *domesticity constraints* keep married women out of the labor force in India. Without changes to these constraints, home-based jobs may represent the most immediate path to increase women's labor force participation.

---

*Jalota: PhD Candidate, Stanford University; Ho: PhD Candidate, Massachusetts Institute of Technology. Many thanks to Grant Miller, Alessandra Voena, Maya Rossin-Slater, and Nicholas Bloom for their insightful guidance and helpful advice on this paper. We are very grateful for comments from Esther Duflo, Soledad Prillman, Erica Field, Amit Khandelwal, Alex Chan, Jasmin Moshfegh, Devansh Jalota, Anuj Khandelwal, Akhila Kovvuri, and seminar and workshop participants at Stanford University over the years. Tanvi Divate provided outstanding research assistance and is a partner on this project without whom this paper would not have been possible. We are grateful to the entire *Rani Work* platform team, which was an excellent partner on the job intervention. Myna Mahila Foundation expertly led data collection for the project with support from Rose Foundation. Project Karya and Microsoft Research supported us with technical assistance, with exceptional support from Vivek Shedashri and Anurag Shukla. We are grateful for the Chembur Gurudwara and the Bhandari family for graciously housing the survey team in Mumbai. Funding for the project was generously provided by the Schultz Fellowship (2019), Hennessy Foundation (2019), the Weiss Fund for Research in Development Economics (2020, 2021), King Center of Global Poverty and Development at Stanford (2019, 2020), Center for Effective Global Action (CEGA) (2022), The Agency Fund (2022), and MIT Solve (2022). This project has human subjects approval from Stanford University IRB (56784) and is pre-registered with the AEA (ID: 0010017). All errors are our own.

†Corresponding author. Email: suhani@stanford.edu

1 Introduction

Less than a quarter of women in South Asia participate in the labor force. This is half the global average of 47% and significantly lower than that of men, highlighting significant gender disparities and economic inefficiencies (Goldin, 2021; Ashraf et al., 2022; World Bank, 2023). In urban India, the labor force participation rate (LFPR) for single women aged 25-29 is 60%, but it is only 20% among their married counterparts, despite similar levels of education (PLFS 2019-2020).[1] Interestingly, at least a third of housewives have expressed an interest in employment, reflecting a potential workforce not fully tapped into (Fletcher et al., 2017). This gap between interest and actual employment persists even as the digital gig economy has grown over the last decade, a sector characterized by short-term, flexible online jobs (Litman et al., 2020; Sinha, 2018).

One explanation for these low labor force participation rates is that the location of most available jobs, predominantly outside the home, introduces various constraints often rooted in gender norms (Jayachandran, 2021). These barriers could manifest as *practical constraints*, such as travel restrictions (Cheema et al., 2019) or the unpaid housework and childcare burden (Greenwood, 2019). However, it is difficult to separate these practical barriers from less tangible *domesticity constraints*, akin to the traditional "purdah" system[2] that enforces female seclusion because married women working outside the home is disapproved of, even in the absence of practical barriers (Papanek, 1973; Bernhardt et al., 2018). Notably, a 2020 World Gallup Survey in 60 countries found that a quarter of male respondents in India opposed women working outside the home, placing India in the bottom third globally for such support—a stark contrast to the global average, where 91.3% support women working outside. (Bursztyn et al., 2023). This raises an essential question for policy intervention: How do practical and domesticity constraints independently impact married women's labor force participation?

This study implements a randomized control trial with 3,200 wives and 860 husbands that attempts to disentangle the barriers women face for employment outside the home. In two field experiments in Mumbai's slum resettlement communities, we compared women's job take-up between jobs at home and jobs at one of 35 newly established offices nearby, which were designed to minimize practical barriers. The job tasks, identical in both settings, required basic skills for data labeling activities, including reading sentences in local languages to support the training of artificial intelligence (AI) models.[3] We established the offices to be women-only, located within a five-minute walk from respondents' homes to improve safety, reduce gender-based violence, and mitigate mobility concerns. The office layout was familiar to the women and situated within their community. Children were allowed in these offices to accommodate childcare needs, with female supervisors available for support.[4] With this low practical barrier experimental setup, we specifically aim to answer these research questions: To what extent can reducing these constraints *increase* married women's labor supply? Which practical and domestic barriers still constrain married women's labor supply in the

[1] In fact, female labor force participation rates have declined in India from 32% in 2005 to 23% in 2022 (PLFS 2022). This ranks India among the world's bottom ten in female labor force participation (ILO, 2020).

[2] Purdah in South Asia, meaning "curtain," is a practice of female seclusion and modesty, varying between Muslim and Hindu communities. It restricts women's interactions with men outside immediate family or marriage, starting at puberty for Muslims and at marriage for Hindus (Papanek, 1973).

[3] These AI jobs are becoming more common in South Asia, yet participation by women is limited (Datta et al., 2023).

[4] Analogous to the presence of family members, like mothers-in-law, at home assisting with childcare.

new setup? Do these barriers restrict married women from all forms of employment, or specifically from roles located outside their homes? Given that the home and office settings were designed to be as similar as possible, any observed differences in job take-up could be due to residual *practical constraints*, such as the ability to multi-task along with housework while working from home, and intangible *domesticity constraints*, such as observability of the job.

To explore our research questions, we created *Rani Work*, a smartphone-based gig work platform, in partnership with the NGO Myna Mahila Foundation and Microsoft Research, that was tailored for this study.[5] This setup gave us full control over experimental conditions, with the application operational only during office hours to ensure a controlled environment, even for home-based jobs. The piece-rate work, offered for 60 days, provided flexibility in work hours and load, with corresponding pay adjustments. Tasks involved speech recordings for identity verification, meeting the needs for equitable AI and diverse language datasets by companies like Microsoft and Amazon, aiming to reduce algorithmic gender bias and develop AI tools that empower local communities (Datta et al., 2023; Hsu et al., 2022). While the gig economy, employing about 12% of the global workforce and set to surpass traditional employment by 2027 (Datta et al., 2023), continues to expand, drawing more women into this sector remains a challenge (Larrazabal et al., 2020). Our approach facilitated job access via smartphones and brought job information directly to women, easing their entry into the workforce.

In the primary experiment, we randomly assign wives to either Work-from-Home (WfH) or Work-from-Office (WfO) jobs and cross-randomize across three wage levels (up to Low ($60), Medium ($150), and High ($300) per month), and to a control group. The wages correspond to two hours of daily work over six days a week. The high wage, when maximized, exceeds the average monthly household income of $250. We varied the wages to trace the labor supply curve for married women and compare it between the home and office settings. We randomly selected 50% of the households for a "husband survey" to inform husbands about their wives' job offers and gather data on their perceptions of their wives' employment.[6] Women eligible for this study were married, unemployed ("housewives"), smartphone users, and capable of performing tasks requiring common skills (e.g., knowledge of speaking a local language). They were drawn from a pool of slum resettlement building communities established by the Government in Mumbai. Treatment assignment was at the individual level and stratified by community and education level. On average, the women were 11th-grade educated with children and were located in neighborhoods with the city's lowest human development indices (UNDP, 2010), influencing our decision to find office job sites within safe walking distance. We established three *specially designed* offices in each community, each dedicated to workers of one wage level to avoid spillovers.

First, we present our primary experiment's core findings on job take-up. Overall, we found that job take-up was significant, as 42% (or 1,187 women) of housewives started to work. The job take-up for office-based jobs was 27%, matching India's female labor force participation (FLFP). In sharp contrast, double the number of women, or 56%, took up the home-based jobs. In other words, women are almost twice as likely to work from home than from these *specially designed* offices, even though

[5] Post-study, the application continues to offer digital microtasks to women.

[6] Notably, there was a 30% refusal rate for this survey, which correlated with conservativeness, suggesting that more conservative husbands, who were less inclined to support their wives working, were also more likely to refuse participation in the survey.

they are women-only, close to home, and allow children. Surprisingly, the labor supply curve for housewives remains unchanged between the two highest wage levels, even when the wages surpass husbands' incomes at $300. There is a 36% increase in office job take-up from the low to the medium wage, but it levels off as wages go from medium to high. Therefore, even a five-fold wage increase, equivalent to an additional month's average salary, does not bridge the job take-up gap between home and office. These results can be explained by the conflicting positive (Goldin, 1994) and negative (Pande and Roy, 2021) effects of offering higher wages to wives, ultimately leading to a plateau in take-up as a function of wage. This indicates that beyond a certain wage threshold, higher pay alone may not incentivize women to work from offices.

Second, we detail the intensive margin results of working from home and office, particularly workers' two-month retention and performance. Approximately half of the workers remain employed in this job for the full two months, with a consistent 50% difference between home and office-based jobs. Overall, 22% of all women offered home jobs complete all tasks compared to 12% of those offered office-based jobs. Despite these differences, office workers show a 20% higher retention conditional on working. Wage levels also impact retention, doubling between $60 and $150 monthly for home and office settings and plateauing after that. Hence, a quarter of women in home-based and one in seven in office-based jobs are likely to complete their tasks when offered at least a medium-level wage. Home-based workers had a 14% lower productivity and 6% lower accuracy than office-based workers, in line with productivity results observed in existing literature (Atkin et al., 2023). This difference is likely due to selection and treatment effects.

Third, we contrast the results on wives' employment with the findings from a parallel experiment involving 450 husbands, termed the *husband experiment*. Husbands were also assigned job offers at the same three wage levels and in home and office settings as their wives in the primary experiment. As 95% of husbands were already employed, the results reflect their job acceptance rates for a part-time supplementary job. This makes the comparison between husbands' and wives' job acceptance more comparable for supplementary household income. For husbands, we find a standard upward-sloping labor supply curve with wages. We find no significant preference among husbands for working from home as opposed to office, with acceptance rates of 35% and 31% (p-value=0.40), respectively. These findings suggest that while wages may drive men's job choices, women's higher job take-up for home-based work likely stems from gender-specific factors.

Fourth, to explore *why* women had a higher job uptake for home-based work despite reduced practical barriers from offices, we analyzed two potential gender-specific factors: (1) persisting *practical constraints*, such as the tangible demands of caregiving and other housework responsibilities, and (2) the impact of intangible *domesticity constraints*, such as the observability and societal disapproval of employment. These intangible *domesticity constraints* refer to social expectations that traditionally confine women to the domestic sphere (behind the *purdah*), often to uphold a positive "social signal" of a husband's provider status (Goldin, 1994; Bernhardt et al., 2018; Papanek, 1973). These constraints can manifest through household-imposed restrictions on women's *mobility and job observability*, effectively limiting women's movement out of the house (Goel, 2023). They can also manifest through *psychosocial pressures* that induce guilt in women who consider working away from home and that emphasize the importance of "good wife" behavior (Dhanaraj and Mahambare, 2022; Goldin, 2021). We first test for the effect of persisting practical barriers on women's lower office job take-up and then run a follow-up experiment that sheds some light on the less tangible constraints.

To test whether the actual burden of childcare and elder-care responsibilities constrained women from working in office-based jobs, we take advantage of the heterogeneity in our sample. Contrary to expectations, women with higher childcare duties were just as likely to accept office-based work as those without. Intriguingly, those with elder-care duties were 20% more likely to choose office jobs than those without, suggesting an unexpected role of the office environment as a respite from home duties. Hence, caregiving duties did not significantly deter women from child-friendly office jobs. Next, to test whether the need to multitask with other household responsibilities prevented women from working in the office, we run a *mechanism experiment*. This aimed to distinguish the convenience of home-based multitasking from the influence of the intangible domesticity constraints on employment decisions.

For the mechanism experiment, we randomly re-assign wives to either a Work-from-Home (WfH) or a Work-from-Office (WfO) job offer or one of three additional ("more costly") WfH variations. These new arms included a "WfH + No Multitasking" arm, restricting women from multitasking with housework and enforcing tasks to be completed in consecutive time blocks by introducing time-sensitive notifications; a "WfH + Check-in" arm, mandating an observable two-minute daily office check-in to unlock the smartphone application; and a "WfH + Check-in + ID" arm, enhancing the visibility of employment with a worker ID badge while walking to the office for the check-in. This design aimed to separate the impacts of multitasking with housework ("WfH + No Multitasking" arm) from the less tangible constraints—observability and mobility restrictions—around women's work outside the home ("WfH + Check-in" arms). The new round of treatment assignments happened at endline, offering women a second round of shorter one-week-long jobs. Women were shown demonstrations and videos about the work and how their job conditions would be enforced before they started to work.

The findings from the mechanism experiment indicate that, although multitasking with housework is a factor, the difference between home- and office-based job take-up may be better explained by observability of the job and other less tangible domesticity constraints. In this second round of jobs, the difference in take-up between home- and office-based jobs increased to 66%. The reduced office take-up compared to the first experiment likely reflects women's increased awareness of home-based opportunities and anticipation of future home offers. We then use the results from the mechanism experiment to explain this gap. The "WfH + No multitasking" arm reduced WfH-only take-up by 8 pp (p-value=0.005), illustrating that the burden of housework may explain about 25% of the uptake gap. The two-minute "Check-in" arms reduced job take-up by 12 pp (p-value=0.000), suggesting that observability and mobility constraints may explain 34% of the difference in uptake between home and office. Results from the "Check-in + ID" and "Check-in" arms were similar to each other. These results suggest that, together, practical barriers and observability constraints could account for approximately 59% of the disparity in job take-up between home and office. The residual 41% may stem from other gender-specific preferences for home-based work or other internal psychosocial pressures influenced by domesticity constraints.

The observability and mobility constraints are likely explicit or implicit restrictions enforced due to intangible domesticity constraints rather than an uninfluenced choice. We provide two key insights to substantiate this. First, a lower job uptake in the "WfH + Check-in" condition is mainly observed among women from less progressive households, as measured by a social norms index, which captures household acceptance of women who work outside the home. Second, husbands' permission for their wives to work seems to be contingent upon job location. Our data shows that while 42% of women stated they were allowed by their husbands to work from home, this approval decreases to 28% for jobs outside the home but within their community and falls to just 18% for jobs outside their local community. Our findings align with the nationally representative 2019 NSS time-use survey, which found that only 29% of non-working women reported leaving their homes even once daily (Goel, 2023). Further, the survey of husbands shows that while at least half were open to their wives working from home, the rest objected to their wives doing the same job outside the home. These numbers reveal a gradient of control based on work location, underscoring the influence of traditional gender roles on women's mobility for work.

Our paper contributes to three strands of literature. First, this study advances our understanding of married women's employment in developing countries by both analyzing constraints and exploring strategies to enhance their labor force participation. We build on previous research on labor demand constraints (Jensen, 2012), household-level practical constraints (Cheema et al., 2019; Greenwood et al., 2023), and the role of social norms (Goldin, 1994; Fernandez, 2007; Olivetti and Petrongolo, 2008; Bernhardt et al., 2018; McKelway, 2020; Jayachandran, 2021; Bursztyn et al., 2020, 2023). In the existing literature on traditional jobs outside the home, disentangling practical constraints from intangible ones is challenging, as both are often intertwined with deeply ingrained gender norms. Our work experimentally isolates the effect of the practical and the less tangible domesticity constraints by providing low-practical-barrier jobs from specially designed offices. Existing literature provides a few strategies to increase women's labor force participation (Jensen, 2012; McKelway, 2020; Field et al., 2021; Dhar et al., 2022; Pandey and Khanna, 2023). We show that modified remote digital gig work—accessible via smartphones, based at or near home, and in line with domestic norms—can engage more housewives in paid work.

Second, with this experimental design, we also add to the literature on female seclusion, where studies show that the practice of *purdah* or *ghunghat* is used to control women after marriage (Papanek, 1973; Hale, 1980; Mandelbaum, 1986; Chowdhry, 1993; Minturn, 1993; Kantor, 2002). Building on the model of separate spheres (Lundberg and Pollak, 1993), we provide experimental evidence consistent with intangible *domesticity constraints* that seclude women at home, suggesting that women might remain out of the workforce even in the absence of typical practical barriers. The preference for lower-wage, home-based jobs over higher-paying jobs outside the home highlights the job location as a key workforce entry barrier, particularly impacting women's earning potential due to the lower uptake of more lucrative jobs outside.

Third, our study contributes to the growing body of research on remote work, which in developed countries often focuses on balancing practical constraints like commuting and childcare with productivity or career growth (Bloom et al., 2015; Kitagawa et al., 2021; Choudhury et al., 2021; Gibbs et al., 2021; Bloom et al., 2022; Atkin et al., 2023; Aksoy et al., 2023; Emanuel and Harrington, 2023). In regions like South Asia and the Middle East, societal norms heavily influence women's employment, presenting unique challenges for remote work. We discovered a significant untapped female labor supply for digital gig work, both from home and in local child-friendly, women-only offices. Addressing the need for remote work solutions tailored to specific groups (Khanna et al., 2010; Joyce et al., 2020; Autor et al., 2020),[7] our experiment with the novel smartphone-based platform *Rani Work* offered digital micro-tasks in a localized, accessible format. This approach allowed us to study job uptake among housewives in a context that minimized practical employment barriers, including the need for personal computers, language barriers, and lack of local context.

Our study demonstrates that improved childcare and transport policies, among other policies that reduce practical barriers to women's work, may not eliminate the gender gap in employment. Given the difficulty in changing social norms around women's work (Jayachandran, 2021), bringing job opportunities into the domestic sphere while considering gender-specific preferences may be the most immediate path to closing the gender gap in labor participation.[8] At least in the short run, accessible digital gig work may be effective at increasing married women's labor force participation.

The remainder of the paper proceeds as follows. We begin Section 2 by providing the experimental context and design, including the primary and husband experiment designs. Section 3 provides information about the data collection process and main empirical specification. We then discuss the extensive and intensive margin labor supply results in Section 4. Section 5 unpacks the mechanisms behind the extensive margin results in the primary experiment. We discuss the implications of our findings and conclude in Section 6.

2 Experimental Context and Design

We first describe constraints to women's work in urban India, including practical and intangible domesticity barriers, many likely stemming from gender norms. Then, we outline a potential set of digital jobs that permit otherwise-constrained women to work within these bounds.

2.1 Practical and Domesticity Constraints to Housewives' Work in India

Married women with a mid-level education living in urban areas in India have the lowest labor force participation rates in the country (PLFS 2019-2020). Most women in India are married, and most married women are not engaged in paid work.[9] Despite substantial gains in women's education in India, with over 45% completing secondary or high school, there has not been increased employment. Mid-level educated women with secondary school degrees have the lowest FLFP of women at any education level.[10]. Further, FLFP is lower in urban areas than in rural areas, likely due to additional labor demand constraints.[11] We discuss the practical and domesticity constraints married women can

[7]We address the need for remote work designs that cater to specific demographics, recognizing that remote gig work platforms like Amazon MTurk reach less than 3% of low-income workers (Kulkarni et al., 2012; Gutheim and Narula, 2012; Gupta et al., 2012).

[8]A study in Pakistan finds a "home-bias" for women also preferring to start businesses from home and forgoing large financial gains to do so (Said et al., 2019).

[9]Even divorced or separated women have higher FLFP of around 30% (Sudarshan and Bhattacharya, 2009), and employed married women generally work fewer hours on average.

[10]These women may find greater value in applying their education to domestic roles than in the market (Afridi et al., 2018) (Kanjilal-Bhaduri and Pastore, 2018; Ghai, 2018) Less educated women, including those who are illiterate or have only primary school education, exhibit the highest FLFP at 56%, often working in agriculture or manual labor. Mid-level educated women might be caught in a paradox, being overqualified for manual labor but underqualified for specialized roles in the tertiary sector.

[11]Agriculture employs a significant number of women in rural areas, while cities lack a comparable industry near women's residences (Malathy, 1989; Sudarshan and Bhattacharya, 2009; Klasen and Pieters, 2015).

experience to be able to engage in paid employment.

Housewives may face practical barriers to work, such as safety concerns, travel, childcare responsibilities, or housework burden (Kapsos et al., 2014). India has the world's highest female-to-male ratio of time devoted to unpaid care work at 9.83:1, placing a majority of the housework burden exclusively on women (OECD Gender Statistics, 2014). Especially after marriage, women are expected to assume most of the caretaking responsibilities (Peters et al., 2019). In urban areas, women may need to spend less time on direct housework responsibilities, yet they may still be *expected* to be "good housewives" by their husbands or in-laws, even when not doing direct housework (Evans, 2014). These intangible domesticity barriers may prevent them from doing anything a "good housewife" would not do, such as engaging in employment (Goldin, 1994; Asadullah and Wahhaj, 2017). However, it is unclear whether these norms are restricting housewives' employment even from home, or only from outside.[12] In other words, we do not have clear evidence that shows whether "good housewives" can be permitted to work in home-based jobs without defying gender norms (or the *purdah* norms).

To understand which constraints are most critical for housewives' employment, we identify real-world job opportunities that can be located either at home or right outside the home, with both setups mitigating practical barriers such as safety concerns, travel, childcare, and housework burden. If only these practical constraints held women out of the labor force, the job take-up from home and office would be similar. Conversely, if other barriers played a more significant role, job uptake from the office might differ.

2.2 New Opportunities with Digital Gig Work

To address the constraints faced by mid-level educated, married women in India's workforce, the burgeoning digital gig economy presents a viable avenue for employment that aligns better with cultural norms and requires basic, generalist skills (Datta et al., 2023; Jayachandran, 2015).[13] While men with similar education can access a variety of urban jobs, women face occupational segregation (Krishnan, 2020); however, digital jobs, seen as more socially acceptable and scalable, could reinvigorate women's participation in the labor market. The digital gig sector, growing due to technological advances, flexible project demands, and organizations' needs for adaptability, has seen significant growth in India, even poised to be higher than traditional employment by 2027 (Chaudhary et al., 2021). The global gig economy employs about 12% of the global workforce and is set to surpass traditional employment by 2027 (Datta et al., 2023). With India leading globally in gig workforce numbers, these online and location-based opportunities offer a potential policy lever to reintegrate women into the workforce amidst a global surge in gig work valued at $455 billion in 2023, a 53% increase since 2020 (Datta et al., 2023).

Micro-Tasking with Data Labeling. Our study focuses on micro-tasking gig work, a burgeoning sector where quick, discrete tasks are performed to train algorithms, offered by companies like Amazon Mechanical Turk, ScaleAI, and Sama, among others. Expected to balloon to a $17.1 billion

[12]More than 75% of non-working women did not leave their home even once a day (Goel, 2023).

[13]There are two kinds of gig work: online freelancing or micro-tasking, or location-based (Kuek et al., 2015) Most of the growth in India is driven by location-based gig work, such as on-demand digital platforms and e-commerce online retailing platforms (Chaudhary et al., 2021).

market by 2030, with India claiming 40% of this space, this growth is fueled by the escalating need for quality data in AI and ML technologies[14] (NASSCOM, 2023). These platforms benefit from a flexible workforce and tap into a vast talent pool while cutting costs and enhancing productivity—key for generating new job opportunities in the digital age. Gig work, with its inherent flexibility, avoids many traditional employment constraints, making it especially suitable for secondary-educated women bound by domestic duties. Despite this potential gateway to economic participation, women's entry into digital gig work remains limited, perpetuating gender disparities and risking the perpetuation of gender biases in AI applications (Datta et al., 2023; Suresh and Guttag, 2021).

Gender Gap in Data Labeling. Despite the growing demand for women in data labeling to ensure fair and representative AI outcomes, the industry has struggled to engage female workers, with only 23% of data labelers being female. This gender gap reflects India's existing FLFP (Difallah et al., 2018). The majority of women in data labeling have transitioned from other employment, reflecting work displacement rather than an increase in FLFP (NASSCOM, 2023; Acemoglu et al., 2023). Gender norms, a lack of awareness about these roles, and limited access to necessary technology prevent many women from entering this field, exacerbating biases in AI that can lead to unfair outcomes (ILO, 2021; Buolamwini and Gebru, 2019; Rajpurkar and Chen, 2020). To mitigate these issues, localized platforms that resonate with the socio-cultural fabric of developing countries are crucial (Datta et al., 2023). They can provide job opportunities tailored to women's circumstances, leveraging smartphones to bypass traditional barriers and tap into the untapped workforce, potentially integrating the substantial portion of women currently absent from the labor force into the gig economy (Sharma and Sindhwani, 2022). Smartphones could make such digital tasks more accessible at scale and even help women to overcome gender stereotypes and biases in the digital gig economy (ILO, 2021). Hence, gig work provided over smartphones and designed specifically according to women's needs has the potential to engage a portion of the 77% of women currently not in the labor force.

2.3 Job Intervention

We developed *Rani Work*, an open-source, smartphone-based gig work platform in collaboration with Myna Mahila Foundation, a women's empowerment organization operating in Mumbai's urban slums.[15] This platform was specifically designed to facilitate women who have been restricted to domestic roles to enter the workforce. Launched in late 2020, *Rani Work* offers women access to a variety of digital tasks aimed at training AI models, including image and text classification, sentiment analysis, and speech recording and transcription tasks.[16] We restructured tasks typically reserved for IT or Business Process Outsourcing (BPO) PC or desktop-use office settings to be smartphone compatible. For our intervention, women contributed speech recordings and transcriptions in Hindi, Urdu, Marathi, along with English, aiding in refining local language algorithms and reducing gender

[14]The market size expanding at a compound annual growth rate (CAGR) of 28.9% from 2023 to 2030.

[15]Myna Mahila Foundation reaches over 1.5 million women across Mumbai's slums, with initiatives in women's health and employment. The platform was piloted in 2021, yielding positive and encouraging results based on feedback and modifications made post the intervention pilot.

[16]With the rise of remote work post-COVID-19, many firms have tapped into micro-tasking, underscoring its scalability. Yet, achieving a profitable model remains challenging.

bias.[17]

An in-house mobile application enabled us to tailor features of the *Rani Work* platform to our experimental design, allowing us precise control over treatment group assignments, application sign-ups, work schedules, targeted notifications, and real-time monitoring of worker activity. This not only helped our understanding of productivity patterns but also ensured seamless operations. By choosing tasks like speech recordings, we facilitated remote identity verification, ensuring that at least the gender of the worker could be confirmed. Furthermore, we established direct bank account payments, ensuring a secure and efficient transaction process for workers. These tasks are presented on the *Rani Work* Android mobile application. While available on *Playstore*, only the workers assigned in the experiment are able to earn income on it. Workers sign up with their phone number and a unique access code they receive with their job offer. Accuracy on the tasks is measured based on a gold standard set of tasks that were already classified and sprinkled in between other tasks. Workers paid for their own internet or data packages to download the tasks.

Digital jobs offered higher market wage rates compared to local work alternatives like decorating bangles, stitching clothes, or making stuffed toys. For digital work, workers can, on average, classify one image every four seconds, i.e. 900 images per hour, and task completion rates for other task types vary depending on their difficulty. At the standard market wage rate of around INR 3 per task and with 60 tasks per hour, women can earn $105 per month, or even up to $150 for two hours of work per day for 6 days a week for a month. In comparison to other forms of work available in the area, women with similar qualifications could get paid around $60 or INR 5,000 for handicraft or other manufacturing work done with more than 6 hours of work per day for 6 days a week for a month.[18] While the job tasks on the digital platform were relatively basic, more complex tasks could allow workers to earn even higher incomes.

To analyze the impact of the practical barriers to women's employment, we designed our study to address each of these concerns: travel, safety, fixed schedules, childcare, and information gaps. In this section, we detail how we mitigated these barriers in both office and home settings.

Travel and Safety Concerns. We established 35 offices within a five-minute walk from participants' homes, significantly reducing travel concerns and enhancing safety. Offices were women-only, so there were no safety concerns related to having male co-workers. The nature of the digital jobs itself did not involve call-center-type interactions with strangers or content moderation work to avoid any cyber-safety-related concerns. For a familiar setting, offices were strategically placed within the community, often in spaces mirroring the layout of the women's own apartments in the uniformly designed buildings. Home-based jobs did not introduce new travel or safety concerns.

Fixed Schedules and Payments. The jobs we offered were part-time (around two hours per day) with flexible work hours, accommodating women's domestic responsibilities. Women could start and complete work any time between 10 A.M. to 6 P.M. daily. Compensation was based on a piece-rate system, so women were paid for the tasks they completed, facilitating easy entry and exit. This

[17] Project Karya and Microsoft Research utilized the generated datasets for language model training.

[18] On average per month, workers in the area with similar qualifications can get paid up to INR 250 ($3.32) per day with a job outside the house, or around INR 35 per hour, as compared to INR 105 per hour with this digital work.

flexibility was standardized across both office and home settings through an automated lock in our mobile application, ensuring consistency in operational hours and payment schedules.

Childcare Concerns. Recognizing the crucial need for childcare support, the local offices allowed children on the premises, with female supervisors present for assistance. In the home setting, women could multitask while having their children around and other family members could assist with child care as needed.[19]

Information Gaps. To bridge information gaps and build trust, we conducted household visits, delivered job details in women's local languages, and provided employee testimonials. Enumerators were also from similar communities and were more relatable to the respondents. This direct communication was vital in both office- and home-based work settings.

There could still be potential confounders, such as the home environment allowing for multitasking with housework and for more fragmented work sessions. We aim to control for some of these factors in the Mechanism Experiment, discussed in Section 5.

2.4 Setting

We conducted our experiments in Mumbai's slum redeveloped communities. Much of our target area was in and around Mankhurd, a neighborhood with Mumbai's lowest human development index (UNDP, 2010). Over 35% of India's population, and 55% of Mumbai's residents (or 10 million people), live in slums or redeveloped colonies (Phuleria et al., 2017).[20] Under the *Slum Redevelopment Plan*, residents are often moved to government-sponsored housing and provided with basic amenities. These redeveloped communities comprise both former slum and non-slum residents, as many property owners choose to rent out their homes. Our study includes both groups, reflecting the widespread low living standards and the pressing need for income, especially in light of the city's soaring living costs and the job losses triggered by COVID-19.[21] (Rambarran, 2014; Chakraborty, 2020)

Despite the communities' diverse backgrounds, women are primarily confined to child-rearing and household chores, with certain groups imposing stricter norms than others. Travel challenges and safety concerns further limit women's employment opportunities; a study in Mumbai revealed that only 17% of women's trips outside the home were for work, compared to 80% for men (Alam et al., 2021). In 2019, only one-fifth of Mumbai's women were employed, underscoring the critical need for accessible income opportunities.

Our sample was generally representative of the urban poor population in Mumbai. On average in our sample, women are 32 years old, 11th grade educated, living in households with five family members with an average household monthly income of INR 20,000 ($244). Their aspirational monthly income is more than double their existing income (around INR 42,000). About 50% of

[19]More than 60% of women from home were supported by other family members, and others worked while their children were sleeping during the day

[20]Globally, slums house between 900 million and 1.6 billion people, accounting for a quarter of the world's population.

[21]Building societies, elected by residents with significant influence, govern these communities. Gaining their support was crucial for our study, which aimed to provide short-term employment to women and conduct extensive surveys. The leaders emphasized the urgent need for more job opportunities.

women had at least one child below the age of eight, and 50% of households own their home. Half of the households belong to the open or general caste and about half are Hindu. Muslims comprised 30% of the sample while Buddhists comprised another 15%. About 40% of the women live with their in-laws while another 20% live close to them. Baseline PHQ-8 scores and the tension standardized index are typical of the population mean.

Gender norms are important in this context.[22] More than 31% of the women believe that, if they make a job decision that their husbands disapprove of, the husbands will shout at or beat their wives. Further, 78% of them think that their husbands would be uncomfortable if they worked with other men. More than a third of women stated that they were explicitly forbidden to work by their husbands.

2.5 Overview of Experimental Designs

We implemented two field experiments, closely aligned in design, to compare job take-up rates among women working from home versus local offices. We then implemented a third experiment involving husbands.

The Primary Experiment. This experiment focused on analyzing women's job take-up by wage level, along with the impact of husband surveys and information assignments (for job offers for their wives) across both home and office settings. Job opportunities were provided for approximately 60 days.

The Husband Experiment. At the end of the study, we elicited husbands' willingness to accept job offers for themselves and their job take-up, presented at the same wage levels and locations as those offered to their wives in the primary experiment. The duration of these jobs was shorter, around a week, with a positive probability of receiving longer-duration jobs in the future.

The Mechanism Experiment. In this experiment, we offered women variations of home-based jobs designed to replicate office-like conditions. This helps us further highlight the mechanisms driving any observed differences in job take-up between home and office settings. This job round lasted between four and ten days, with a positive probability of receiving longer-duration jobs in the future. We discuss the experiment design in the Mechanisms section.

Each job opportunity was presented in two distinct rounds corresponding to the two main experiments. The overall design of these experiments is illustrated in Figure 1.

[22]Although the norms may be less extreme and observable in rural areas where a homogeneous setting could reinforce certain norms.

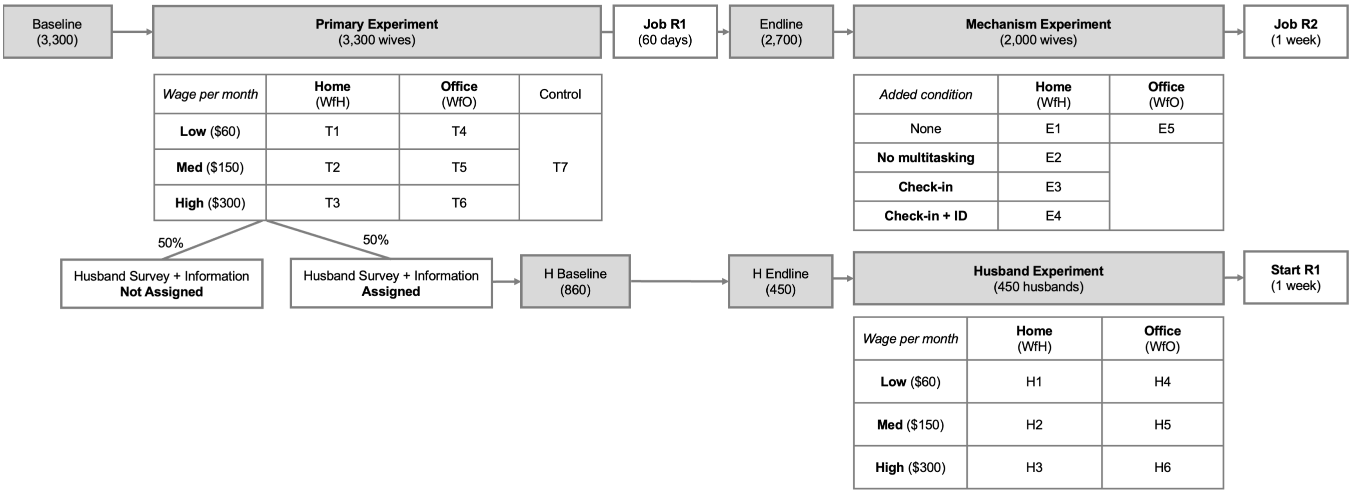

Figure 1: This figure shows the full experimental design, including the primary experiment (on the left) and the follow-up experiments at Endline (on the right). After the baseline survey, women were randomly assigned to one of six job offers, or a control group. The job offers included a unique combination of a location (home or office) and wage level (low, medium, or high). Households were also randomly assigned to receive a Husband Survey or not (split in half across each arm). After the initial assignment, women complete the Round 1 jobs, then the Endline survey, followed by re-assignment into the mechanism experiment arms. Husbands were also assigned to their wives' primary experiment arms at Endline.

In the following section, we delve deeper into the Primary Experiment, providing a more thorough overview of its design and outcomes.

2.6 Primary Experiment Design

At the end of a baseline survey of 3,200 married households, wives were randomly offered one job contract, either to Work-from-Home (WfH) or Work-from-Office (WfO). They were cross-randomized to one of three monthly wage levels: Low ($60), Medium ($150), and High ($300)[23] and to a control group. The High wage is five times that of the Low wage and around the average wage of the married men in these communities. Women had an equal probability of being assigned to each arm and to the control group.

As wages increase, the standard labor supply curve would predict increased job take-up. However, if women are constrained by factors other than wages, this monotonic relationship may not be as certain. We manipulated wage levels for three purposes: firstly, to evaluate whether insufficient financial incentives were a barrier for non-working women to enter the labor force; secondly, to discern the driving factors behind men's and women's labor supply based on location; and thirdly, to investigate whether very high wages, surpassing those of their husbands, might contradict a "male breadwinner" social norm (Pande and Roy, 2021), potentially leading to a decrease in job acceptance at higher wage levels, indicative of a non-monotonic relationship between job take-up and wage.

The job tasks given to women at home or in the office are the same. Although the job task is offered as a piece rate, i.e., workers get paid depending on the number of tasks they work on and their accuracy in those tasks, respondents found it easier to understand a monthly estimated amount than an hourly or daily wage rate. Hence, the Low wage arm offer was stated as "You can earn up to INR 5,000 per month if you work around 2-3 hours a day for 6 days a week," and they were shown a brochure that highlighted the wage to make it even more salient. The low payment offer of INR 5,000 ($60) is close

[23]The actual wages were provided in INR at INR 5,000, INR 12,000, and INR 24,000, respectively. The USD amounts are rounded estimates and shown for simplicity.

to what other typical, manual jobs from home currently pay women in Mumbai. The Medium wage arm offered up to INR 12,000 ($150) monthly, close to the job opportunities high school-educated women could get outside. The High wage arm offered up to INR 24,000 ($300), which is on par with their husbands' salaries (or even higher). The husbands, on average, earn around INR 19,000–20,000 per month in this sample.

Depending on the treatment arm assigned, the women are immediately shown their job tasks and wage rates. Each of the treatment arms is described in more detail below.

Work-from-Home (WfH) Treatments 1–3: WfH was offered in three treatment arms: **Treatment 1**: WfH with Low wage, **Treatment 2**: WfH with Medium wage, and **Treatment 3**: WfH with High wage. In the WfH arms, workers are offered a job contract to work from home on their own smartphones. They can make queries on WhatsApp or over a phone call to a dedicated call office. All work was allowed on the smartphone between 10 A.M. and 6 P.M. only, and the mobile application was locked at all other times (and on Sundays) to be comparable with the office timings.

Work-from-Office (WfO) Treatments 4–6: WfO was offered in three other treatment groups: **Treatment 4**: WfO with Low wage, **Treatment 5**: WfO with Medium wage, and **Treatment 6**: WfO with High wage. In WfO arms, workers are offered a job contract to work from a local, digital job office on their own smartphones. Women are not provided with a smartphone device at the office. Three offices were established per area since each office was dedicated to workers of a single wage level in order to avoid spillovers. Hence, women in each of the three wage levels were assigned to specific offices that were strategically located in different buildings so they would not overlap. The women selected to work from an office would sit with other female workers and a female supervisor,[24] who monitored the overall activities, ensuring limited contact between workers but not interfering with the job tasks. Supervisors gave women a daily code that unlocked their mobile applications for a couple of hours to work from the office. Women chose for how long and when to come into the office to do the job. They logged in their time of entry and exit at the office in a log book, and they were only paid for the work conducted while at the office. Workers were recommended to call their dedicated call office or to use WhatsApp to submit their queries. Women could bring their children to the offices, and the children's attendance was recorded as well.

Husband Survey Assignment. Additionally, 50% of the households were cross-randomized to a husband survey, which not only shared details about the wives' job offers (for those in the treatment groups) but also contained a section to gauge the men's preferences regarding women's work. Regardless of the husband survey assignment, wives in both conditions retained the discretion to discuss their job offer with their husbands. Women were notified about the potential husband survey during the baseline survey, prior to making their job offer decision. Given the pervasive communication challenges in this setting and the potentially significant lack of trust between husbands and wives, the husband survey emerged as a more reliable way for husbands to learn about the jobs than their wives were. Over 90% of the women typically discussed job offer details with their husbands. Nonetheless,

[24] The presence of a female supervisor may also be favorable for female labor force participation (Subramanian, 2019).

women had the autonomy to withhold specific job-related information, such as the wage level, or even to request that their husbands be excluded from the survey and not informed about the job details.

Control Arm. The control group was around 14% of the total sample, since all households were equally divided between each of the seven arms (six treatments and one control). The control group also received the baseline and endline surveys but did not receive the job intervention offered in the primary experiment. Instead, they are simply asked about preferences for a future job.

Digital Payments and Bank Accounts. All workers were paid digitally through the mobile application directly to their bank account or mobile wallet. We encouraged women to transfer the money to a bank account in their own name. However, 25% of women in our sample did not have a bank account for transferring the wages. We partnered with a local private bank, YES Bank, to open bank accounts for any of the women who wanted to have their own accounts but did not yet have one. Through this process, we opened 200 bank accounts. Women were not aware we would help them open their bank accounts prior to them receiving the payments. They were only informed after they started work on the platform and needed the account to receive earned payments. Hence, we do not expect women to start working in expectation of opening bank accounts.

Job Acceptance and Start. Since the primary outcome for this study is women's job take-up, we measure it across multiple stages: (i) Day 1 Survey: at the end of the baseline survey women are asked whether they accept the job offer, (ii) Day 2 Survey: one or two days after the baseline survey, surveyors return to confirm the job offer decision, (iii) Started work: whether the women start to work on the mobile application, and (iv) Worked more: whether they actually spend significant time working (i.e. $\geq$ 100, 500, 1000, 10000 tasks). We use the "Started work" measurement, or (iii), for most of the extensive margin analysis, since that most accurately measures the decision to start working. After the women are offered jobs during the survey, they can take a few days to think about their responses and download the application. After that period, we call them directly and mark whether they reject the job or are continuing. For our purposes, they are marked as finally accepting only if they actually start working on the job.

2.7 The Husband Experiment Design

To evaluate whether the observed disparities in job acceptance are exclusive to women, we extended similar job offers to husbands assigned to surveys. These offers mirrored those presented in their wives' primary experiment, both in terms of location (home or office) and monthly wage level ($60/month, $150/month, or $300/month). Husbands were surveyed at baseline and endline, with the latter including the job offer. Accepting the job triggered a requirement to download the mobile application and complete an initial set of tasks.

However, an overall lower job take-up among husbands might be expected due to pre-existing employment; 97% of husbands in our sample were already employed. As a result, they may view the one-week job opportunity as supplemental income rather than a primary employment option.[25]

[25] With the *Rani work* platform attracting more projects, opportunities for longer-term engagement are anticipated for

Further, the experimental design varied between genders as the Husbands received offers approximately four months after their wives and the employment duration was limited to one week initially. Around 30% of husbands refused the survey and another 15% were not available. Hence, we surveyed 850 husbands.

3 Data and Empirical Specification

We explain how the data was collected, including sample, treatment assignment, and survey rounds, and then show our empirical specification.

3.1 Data collection

We discuss the data collection process in stages: sample and treatment assignment, listing and eligibility, stratified random sampling, baseline and endline surveys, and worker activity reports. Data collection along with the field management was led by local data collection teams from Myna Mahila Foundation and Rose Foundation.[26] All surveyors introduced the household interview as a survey about women's employment status and opinions, and a potential job opportunity either for now or in the future. The male surveyors introduced the household interview to understand the husbands' perceptions of their wives' work status. Both wives and husbands were surveyed at baseline and endline through in-person household surveys.[27]

Surveys were administered verbally, either by the door of the homes or inside, and in private, with only a surveyor and the individual being surveyed present.[28] Surveys were always conducted by an enumerator of the same sex, complying with the local gender norms of avoiding private interactions with non-family members of the opposite sex. Surveyors introduced themselves as affiliated with our NGO partner Myna Mahila Foundation, which participants may or may not have heard of. Distrust is pervasive in Mumbai slum communities, where fraudulent behavior by external parties is unfortunately common. Surveyors introducing themselves as affiliated with an independent survey firm rather than an NGO might only create further distrust.[29] However, the surveyors did not affiliate themselves with the job provider, *Rani Work*, and the job intervention team was kept independent from the survey team.

3.1.1 Sample and Treatment Assignment

The experiment was conducted in thirteen slum redeveloped communities in Mumbai across 478 buildings. The selected areas were located around Mankhurd, Nahur, Vikroli, Wadala, Kurla, Kanjurmarg, Govandi, GTB, Chembur, and Bandra. These communities are situated at varying

both women and men who participated in this study.

[26] Rose Foundation recruited and managed many of the female surveyors and supervisors from rural Maharashtra, while Myna Mahila managed the surveyors and rest of the research team from Mumbai.

[27] When we could not connect with husbands in person, even after multiple visits, but they could be available over the phone, we interviewed them by phone call. About 40% of husband interviews were conducted over the phone.

[28] However, there were some exceptions when someone else from the family insisted on being present for the survey. We marked those households as "supervised." Further, some of the husband's surveys, particularly at endline, were conducted by phone since they were not available at home most of the time.

[29] In our knowledge, no one refused the survey due to Myna Mahila's reputation (but some agreed to take the survey because of their knowledge of the NGO).

distances from one another, all located within the city limits of Mumbai. They were selected from a Government list of all slum redeveloped colonies based on (i) having a medium- to large-size slum redeveloped building settlement, as we needed at least 100 eligible households per area to have a sample size large enough for stratified randomization, (ii) being within the existing reach or potential future reach of our NGO partner, and (iii) having available spaces for establishing local offices for WfO treatments. Once the areas and buildings were identified, our NGO partner, Myna Mahila Foundation, provided an orientation about the new employment project to community leaders and building society members to seek their approval. These orientations were held at the building-level and through community meetings along with local leaders. Once we had written approval from every building society to continue the study,[30] and permissions from the local police stations, we started the listing exercise.

Listing and Eligibility. The purpose of the listing survey was to identify eligible women for the study by visiting households door-to-door. These listing surveys took place between May to August 2022 covering about 24,500 households i.e. all households in the buildings with permission to do the study.[31]

Women were eligible for this study if they were (i) married, (ii) between 18 and 45 years old, (iii) in possession of a smartphone or access to one for at least two to four hours a day, (iv) able to correctly complete at least two out of three Rani Work tasks (on a printed copy), (v) living with their husbands (not in their maternal homes), (vi) living in either a slum or a slum redeveloped colony, (vii) self-identified "housewives" who did not do significant paid work (no more than 20 hours a week), (viii) the only woman living in a given house enrolled in this study. To check for eligibility, women were asked to perform three actual job tasks using printed copies. Those eligible for the study were then included as part of the sample for random assignment in preparation for Baseline surveys. Around 15% of all households visited had an eligible woman for the study. Most ineligible women were not able to successfully do the tasks, often because of lower education levels or a lack of knowledge of English, Hindi, Urdu or Marathi.

Stratified Random Sampling. Around 3,700 women were listed as eligible for the study. Treatment assignment was done at the household level. Each of the resettlement communities had different characteristics with regards to social norms, religious sentiments, safety, size, proximity to other jobs, etc. Hence, it was essential to stratify the treatment assignment by area. Further, educational qualifications were not part of the eligibility criteria, but could be important for the employment outcomes we are interested in. Hence, we also stratify by two education levels: (1) completed 10th grade or below, and (2) completed 11th grade or more (e.g. a Bachelor's or Master's degree). While we suspect having children could also be important, most of our sample (all married women) had children, so it was not as important for stratification. Using area and education level as the stratification variables,

[30]This was done through individual meetings, not together, to avoid inter-building conflicting interests and dynamics. A few building societies refused to participate in the project as well, and they were excluded from this study entirely. The reasons for refusal tended to be political (where we did not align with a political party for provision of jobs for women, and they wanted the combined branding to approve), or a clear denial for doing any research in their building. We observed around 20% of the building societies refused any form of survey in their building.

[31]If households were locked even after three tries on different days, they were not included in the listing sample.

we randomly assign women to one of seven arms: six treatments and one control. Participants had an equal probability of being in any of the seven arms. Further, we randomly assign 50% of the households to husband surveys within each treatment and control arm. Each household had equal probability of being assigned to a husband survey. Once the random assignments were made, the listed households were visited again for the baseline surveys.

Baseline surveys were completed between October 2022 and February 2023 by area, followed by endline surveys between January to May 2023. Tables 2 and A2 test for balance across treatment and control arms across various baseline characteristics. Almost all differences are statistically insignificant, suggesting that randomization was successful. Further, attrition was not treatment-specific at the Endline.

3.1.2 Surveys of the Women

Baseline Surveys. Baseline surveys for wives were conducted in two parts for each woman: Day 1 and Day 2 surveys. The Day 1 survey was a 40-minute to hour-long survey covering the following modules: (i) household demographics, (ii) occupation, (iii) willingness to work and job aspirations, (iv) dignity, (v) social norms, (vi) mental health and well-being, (vii) agency, (viii) time use, (ix) the job offer, and (x) enumerator's observations on family interactions during the survey. Only after completing the survey, that is, modules (i)-(viii), surveyors learned the treatment arm the household was assigned to (one of the six treatments or the control). If the household was in the control arm, they explained to them about a future job opportunity and were asked about their preferences for the job to compare with the treatment groups. If the household was in one of the treatment arms, they congratulated the women on receiving a job offer, and explained the job offer details along with the job contract, including wage and job location. If a woman accepted the job on the spot, she received a job voucher (Figure B4) and a unique access code tied to her treatment arm to be able to access the mobile application with a treatment-specific view. She could download the mobile application, add the access code, and start to explore the platform immediately. Nevertheless, women on Day 1 were told that no matter what response they gave us that day—that is, to accept or reject the job offer—we would come back the next day for a final confirmation, in case their response changed.

During the survey, women make decisions based on partial knowledge of their actual ability to work in the job. Once they need to start working, they may learn about constraints they were not aware of earlier. We get women's initial decision to start working on Day 1, before they discuss with others. The Day 2 final job decision is collected one or two days later, after they may have discussed the job with others. During the Day 2 survey, we also better understand the reasons for job rejection across treatment arms. From the pilot experiment we conducted with 445 women in late 2021, we learned that women may have never spoken about their job or paid work to anyone before, so they may not know whether they can really work in a job on the first day. Even giving them a day or two could help them consult others, learn others' reactions, know the stakeholders in their own family or community who get involved in decisions about her work, and then update their beliefs to be closer to reality. Having two decision points from the Day 1 and Day 2 surveys could help us understand the difference in responses when on Day 1, the woman makes her decision alone, and on Day 2, she might be influenced by conversations with others. Ultimately, we observe whether or not she finally starts the job as the final decision point. The Day 2 survey had the following modules: (i) job offer, (ii) reasons for the job decision, (iii) process of decision making, (iv) financial inclusion and payments, (v) application download, and (vi) enumerators' observations on family interactions during the survey.

The experiment sample at baseline was 3,200 women. About 90% of all eligible women completed the baseline survey, as 5% of women became ineligible by the time of the baseline survey since they may have relocated to a different community (or gone back to the village) or did not have access to a smartphone anymore, and another 5% refused the survey due to lack of interest or trust in participating in the study. These were not different across treatment arms.

Endline Surveys. Endline surveys were implemented from January to May 2023 as hour-long surveys for each household. The endline survey was similar to the Day 1 baseline survey, only with six additional modules: (i) future employment preferences, (ii) take-it-or-leave-it round 2 job offers, (iii) ranking jobs and coins exercise, (iv) job perceptions and experience (treatment arms), (v) use of earned income, and (vi) round 2 job offers. The endline completion rate was 81%, and the attrition was not different by treatment.[32] At the end of the endline surveys, two-thirds of the households were provided with a subsequent round 2 job offer as described in Experiment 2 in the Mechanisms section. The remaining one-third of households were provided with only a Work-from Home or Work-from-Office offer to understand women's continued preferences for taking up future work from either location. At the end of the endline surveys, women could again sign up on the mobile application with a new access code and begin work again, but for a shorter job duration.[33] Surveyor assignments to endline participants minimized experimenter demand, where participants were mostly surveyed at endline by a different surveyor than the one who had conducted the baseline survey with them.

Unlike the baseline survey where job offers were made at the end, the endline survey presented women with five job options in a take-it-or-leave-it (TIOLI) format, using a strategy method. After deciding on each offer, participants ranked these jobs in their preferred order. This strategy method was key in the actual job offer implementation. Additionally, for utility elicitation, we conducted exercises like the coin allocation task, where each woman received 10 "coins" to distribute across the job options as desired. They could focus all coins on one option or spread them among several. This task, although not financially incentivized, was taken seriously by participants. Data from these preference-elicitation exercises serve as additional support for our main findings regarding job uptake.

3.1.3 Worker Activity Reports

Once women downloaded the application and entered their unique access code, they accessed their unique view of the mobile application. They could start doing the tasks that were available to them. Their activity on the platform, from the time they log in to the time they exit, is automatically monitored and captured. This includes time spent on each task, idle time, number of tasks completed or skipped, accuracy of each task, and wages earned. In addition, women could call a "Rani call center" if they had queries with regard to their work or other challenges, and all calls were monitored

[32] Typically in slums the attrition rates can be higher than usual due to households shifting areas. Refusal rates were about 9.8% for the endline survey.

[33] Due to budgetary constraints, the length of the job in the second round was shorter (one week rather than one or two months).

and queries recorded. Finally, when women came to the office for work, their attendance along with any accompanying children was recorded daily. These three worker activity reports of (i) intensive margin activity on the platform, (ii) call center data, and (iii) office attendance, are combined with the household survey data for analysis.

3.1.4 Husband Surveys

In each household assigned to a husband survey, eligible women and their husbands were surveyed. Husbands were administered shorter surveys at both baseline and endline capturing the following modules: (i) occupation and income, (ii) future employment preferences for wife, (iii) take-it-or-leave it round 2 job offers for wife, (iv) ranking jobs and coins for wife, (v) dignity, (vi) social norms, (vii) willingness to work and aspirations, (viii) job perceptions and experience (treatment arms), (ix) use of earned income, (x) job offer for self, and (xi) application download. In the end, we were able to survey 60% of husbands, since the rest opted out or were unavailable. While husband survey refusals are not different across treatment arms, only more progressive husbands responded to the survey. More than 90% of the husband survey refusal was due to husbands dissenting their wives doing paid work.[34]

The final dataset was merged using the wives' household surveys, husbands' household surveys, and the wives' activity on the job platform.

3.2 Empirical Specification

Our primary analytical approach is an intent-to-treat analysis, focusing on job take-up as the main outcome of interest. We run the following regression specification for this study.

$$Y_{i,s} = \sum_{j \in L,M,H} \alpha_j WfH_j + \sum_{j \in L,M,H} \beta_j WfO_j + \delta X_i + \mu_s + \varepsilon_{i,s} \tag{1}$$

$Y_{i,s}$ denotes a binary variable indicating the employment outcome for woman i and strata, s, capturing whether she started working. The variables WfH^j and WfO^j represent indicators for assignment to the Work-from-Home and Work-from-Office treatments at wage levels j, which can be Low (L), Medium (M), or High (H). To control for baseline characteristics, we include X_i, a set of covariates for the woman i, selected from 30 potential variables using the post-double-selection (PDS) Lasso method as proposed by Belloni et al. (2014) and implemented by Ahrens et al. (2018). The term μ_s accounts for stratum fixed effects. We allow for the clustering of standard errors at the stratum level with $\varepsilon_{i,s}$ representing the error term, and we omit the constant from the specification to enable direct comparisons between all treatment conditions. This setup facilitates an assessment of the differential impacts of being assigned to work-from-home or work-from-office jobs at various wage levels while controlling for baseline characteristics and fixed effects.

[34] We informed wives if their husbands were going to be surveyed in the Day 1 survey at baseline. Some women declined to have their husbands surveyed, so those husband surveys were not attempted.

4 Labor Supply Results

First, we show the job take-up results from the Primary Experiment, which is the main focus of the paper. Then, we look at the intensive margin results from the same experiment and show results from our heterogeneity analysis determining which women are most likely to enter work. We then discuss the results from the Husband Experiment.

4.1 Job Take-Up

We observe results on the extensive margin and use the binary variable of starting the job on the platform as the main outcome variable. We refer to the main outcome as "Started work," where women start performing tasks on the platform. While at baseline none of the women in the sample were employed, with the job offers, overall 42% of women (1,187 women) started to work. To measure extensive margin job take-up, we also cross-check our results by looking at women's start of work after working on the platform for at least 10, 100 or 500 tasks, which is a few hours of work. The relative comparisons across treatment arms remains similar. First, we discuss the job take-up by location (taking an average across all wage levels), then we show the results by wage level and location. We then show the difference in job take-up from the survey decisions women made. Finally, we show some heterogeneous results to understand which subgroups of women might be responding differently to job take-up by treatment.

4.1.1 Job Take-Up from Home and Office

When women were offered these home-based digital jobs, 56% of them started to work. In sharp contrast, for office-based digital jobs, only 27% of women started to work, more closely mirroring India's FLFP. In other words, women are almost twice as likely to work from home than from offices. Figure 2 demonstrates this 107% increase in job take-up between home and office. Even though the women-only offices are close to home, that is, within the same community and a short two- to five-minute walk from their houses, and they allow children, only a quarter of women start to work from the office. Hence, factors other than the ones we control for in the experiment design from offices may be keeping women from work.

Similar to the primary experiment results, we find that WfH has triple the take-up from WfO in the mechanism experiment as well (described in the Mechanisms section).

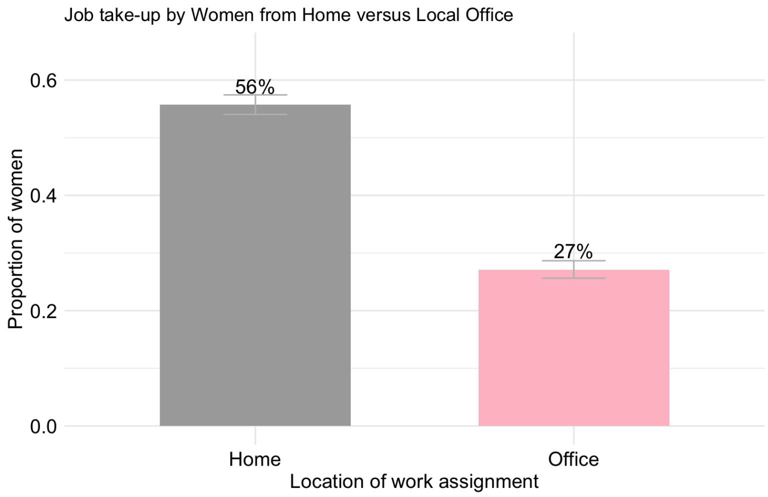

Figure 2: This graph shows the difference in the proportion of women starting work when they are randomly assigned to a digital job either from home or from local offices. The error bars represent 95% confidence intervals. The orange bar represents take-up from home and the pink bar represents take-up from local offices.

4.1.2 Job Take-Up by Wage Level

Even as wages increase up to five times, surpassing their husbands' incomes, women are not increasingly likely to enter the workforce. This pattern persists in both home and office settings, though there is a small increase in take-up from the low to medium wage. Figure 3 shows that job take-up for home-based work varies between 54% and 58% across different wage levels, with a slight, statistically insignificant drop from medium to high wages. A non-monotonic relationship between wage and job take-up is observed when husbands are not assigned to a survey (detailed in the Mechanisms section). For office-based jobs, job take-up ranges from 22% to 30% across wage levels. The 36% increase from low to medium wage is significant, suggesting an upward-sloping supply curve, but job take-up flattens from medium to high wages. Hence, if women are paid $240 (or INR 19,000) more, which is equivalent to an increase by one month's average salary, it does not close the gap in job take-up between home and office.

We use the take-up rates at the three wage levels to calculate the wage elasticity at the extensive margin. For Work-from-Home, married women's wage elasticity in participation is -0.001, or close to zero[35]. Hence, women are relatively inelastic to wage at the extensive margin in this experiment[36]. These results can be explained by the conflicting positive (Goldin, 1994) and negative (Pande and Roy, 2021) effects of offering higher wages to wives, ultimately leading to a plateau in take-up as a function of wage. This indicates that beyond a certain wage threshold, higher pay alone may not incentivize women to work from offices.

[35]Wage elasticity of labor supply at the extensive margin was calculated using the following formula: Wage elasticity = $\frac{\text{\% change in probability of starting job}}{\text{\% change in wage}}$.

[36]Variations in women's wage elasticities, often indicating increased career focus, contrast with lower elasticities among male primary earners (McClelland et al., 2014). Our study focuses on middle-educated, married women, emphasizing the importance of job location over wages for their workforce participation. This is consistent with the low wage elasticities typically seen for women in the United States (Blau and Kahn, 2007; Kumar and Liang, 2016; Qin et al., 2015).

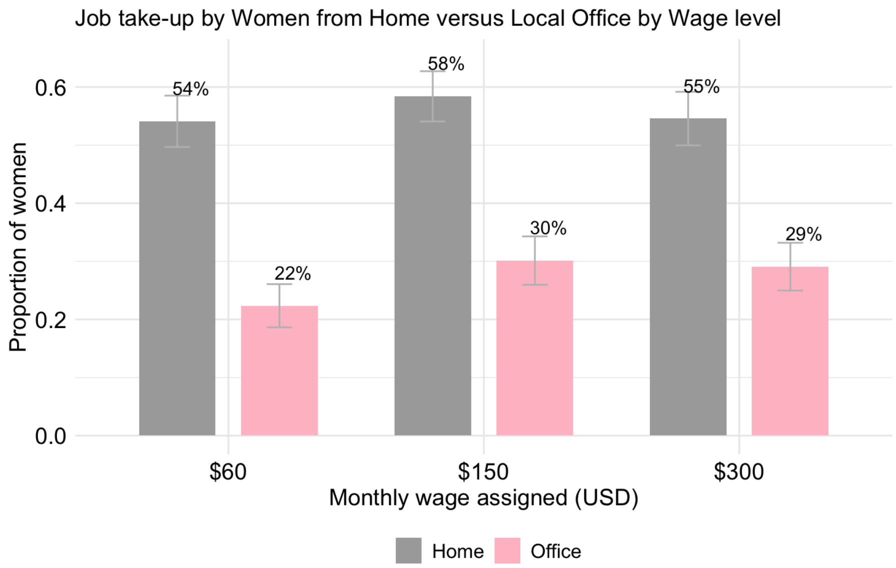

Figure 3: This graph shows the difference in proportion of women starting work when they are randomly assigned to a digital job either from home or from an office for low ($60), medium ($150), and high ($300) monthly wage levels. The error bars represent 95% confidence intervals. The orange bar represents take-up from home and pink bars from local offices.

However, this job take-up with wage is not true for men, since a similar exercise with husbands reveals a standard monotonic relationship in job take-up with wages, which is also not different between home- and office-based jobs. Husbands are much more responsive to wages at the extensive margin than women for a part-time supplementary job. We discuss this more in the Husband Experiment Results section.

4.2 Intensive Margin Results

The primary aim of this study was to provide a causal estimate of offering work-from-home jobs on women's labor supply at the extensive margin. We show that more than 50% of women enter with home-based work. Next, we analyze the retention rates and performance of these women over a two-month period by location and wage level.

4.2.1 Retention

Over time, about half of the women stay in the job till the end, and the difference in participation from home and office remains similar. While 42% of women take the job overall, conditional on starting work, around 87% of them stay after two or three days, and 41% of them (482 women) complete all the 15,000 tasks over 60 days. Overall, 22% of women offered home-based jobs complete all tasks, as opposed to 12% of all women offered office-based jobs. While the difference between home and office take-up and retention remains similar, conditional on starting work, the retention rate for office-based workers is 20% higher than from home (50% versus 40%, respectively).

Further, retention rates are affected by the wage level offered, up to a threshold. From Figure 4, we see that retention doubles when the wage increases from $60 to $150 per month for both home-based work and increases by 150% with office-based work, but plateaus after $150. The upward sloping labor supply curve is more evident across the three wage levels for home-based jobs. This implies that one in four women offered a home-based job and about one in seven women offered a office-based job are likely to complete it if offered at least the medium wage. This is in line with the average market wage for such jobs around $120-150 per month.

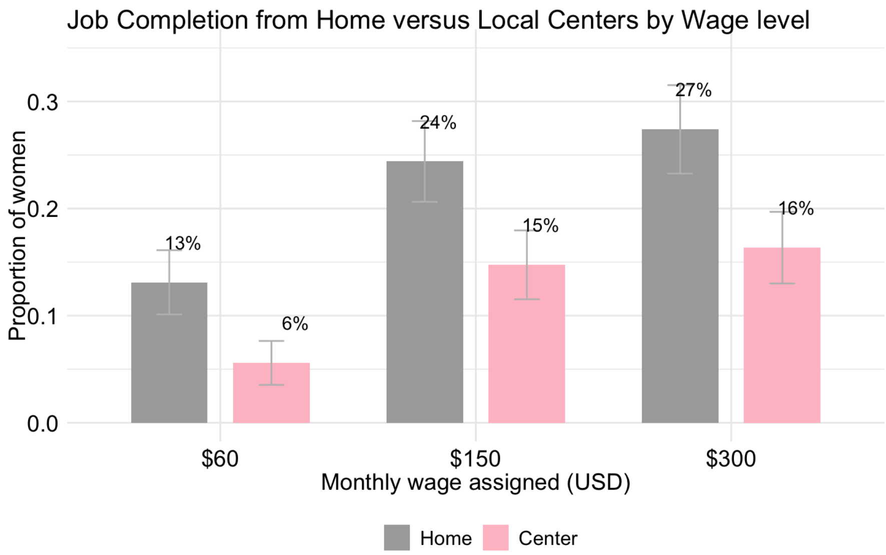

Figure 4: This graph shows the difference in the proportion of women completing work when they are randomly assigned to a digital job either from home or from an office for low ($60), medium ($150), and high ($300) monthly wage levels. The error bars represent 95% confidence intervals. The orange bar represents take-up from home and the pink bar represents take-up from local offices.

4.2.2 Productivity

We next look at the productivity of working from home as compared to the office. As Table 1 shows, women working from home or office spent about the same number of minutes on average working on the platform. On average, women spent 2,556 minutes working in the job over 27 days and completed 8,581 tasks (43% of the total) across home and office. However, women working from home are paid INR 1,180 ($15) less than women from offices, since they complete 1,132 fewer tasks on the platform. Hence, WfH productivity is lower by 0.448 units, or a decrease of around 14%, as measured by the total number of tasks completed by total time taken. Women's accuracy for the speech task type is about 0.06 units lower in WfH, or 9% lower than for women in the office-based arms.

Table 1: Intensive margin results of working from home

	Minutes (1)	Pay (INR) (2)	Tasks (3)	Productivity (4)	Accuracy (Speech) (5)
Home	−68.972	−1179.957***	−1131.887***	−0.448***	−0.056*
	(123.883)	(421.827)	(420.475)	(0.073)	(0.030)
Constant	2095.632***	5734.551***	7496.389***	3.054***	0.686***
	(407.710)	(1155.722)	(1318.991)	(0.219)	(0.087)
Observations	1186	1187	1186	1186	841

Notes: This table shows the results on the intensive margin, that is, the effect of working from home compared to working from the office. Women working from home have lower productivity. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Overall productivity is higher in offices as in Figure 5 since there is a distributional shift to the right for women working from offices. This is likely due to a combination of both a selection and a treatment effect. While the study was not designed to separate these effects, in our analysis of the impact of working from home on productivity, Lee bounds estimation reveals a significant selection effect (Tauchmann, 2014). This was evidenced by a high trimming proportion of 50.39%. The treatment effect range, statistically significant at both ends, varies between a decrease of 1.32 and an increase of 0.44 tasks per minute, highlighting the potential for both negative and positive selection into home-based work. Any negative treatment effects at home could be due to distractions in the household with multitasking, or the office set-up may offer learning opportunities from co-workers. As part of the experiment, we had not imposed strict monitoring over quality or provided formal training programs to women, which could motivate them to be more productive from home.

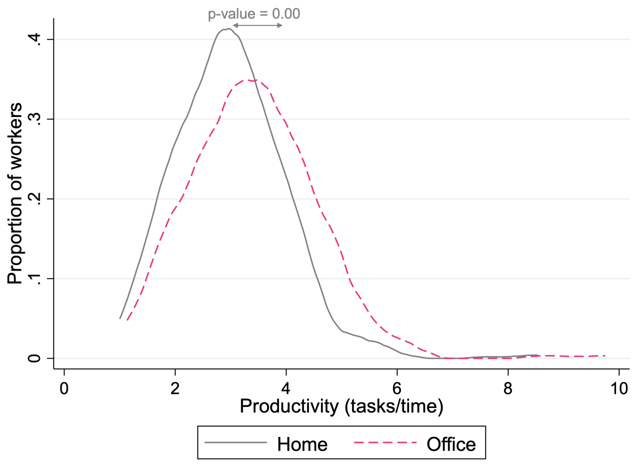

Figure 5: This density plot shows the Round 1 productivity distributions for women who worked from home and from office. Women who worked at an office were more productive than women working from home.

Further, as expected by standard labor supply models, women who are paid low wages work fewer hours than women who are paid medium or high wages, as seen in Table 3 in the Appendix. Women in low wage arms spend almost 46% less time (1,075 fewer minutes) on average working on the platform than women in high wage arms and have 13% lower productivity. Women in medium and high wage arms have similar productivity, task completion, and time spent on the platform.

4.3 Heterogeneity Analysis

Next, we explore what types of women were most likely to start working and to complete work, from home and office. We test for heterogeneous treatment effects by a few indicators, including husbands' income, previous work experience, mental health indicators, husbands' survey responses, conservativeness, women's agency, household structure, socioeconomic status of the household, and demographics like religion and caste.[37] The *purdah* norm, although present among both Muslims and Hindus, may limit women's interactions in different ways. While Muslim purdah restrictions do not apply within the immediate kin unit, but only outside it, the Hindu purdah is based on a set

[37]Notably, previous work experience does not appear to influence job take-up; the 36% of women in our sample with prior work experience (mostly before marriage) demonstrated similar take-up rates to those without any previous work experience. Additionally, living arrangements, such as residing with in-laws, do not seem to impact job acceptance decisions. Qualitative interviews indicate that the flexibility and unobservability of the job, as it is performed on smartphones, minimizes family tensions that might arise with more visible forms of employment. Furthermore, job take-up does not vary significantly across different caste categories, whether open or scheduled.

of avoidance rules between a woman and her male affines (Papanek, 1973). Further, while Muslim seclusion begins at puberty, Hindu seclusion begins with marriage. However, economic pressures may compel some women to break purdah norms for income. Hence, women from lower socio-economic backgrounds may prioritize economic needs over strict adherence to purdah.

Consistent with our expectations, our findings indicate that women from lower-income and more progressive households are more inclined to work. There is a 4% decrease in job take-up for wives of husbands earning above the median income. Women from higher income households are particularly less likely to accept office-based jobs at low wages. The husband's survey response proves to be a crucial determinant of the wife's job acceptance, reducing her likelihood of working by 37% if he declines to participate—a trend more prevalent among higher-income husbands. Further, we find a 10% increase in take up for women from progressive households, and a differential retention in the job by religion. At low wages, Muslim women participate in work to a similar extent as non-Muslim women, regardless of whether the job is home-based or at an office. However, their uptake significantly declines as wages increase to medium and high levels. Women from less progressive households are more likely to cease working after initially accepting a job, with Muslim women showing a higher tendency to drop out from both home and office jobs, and this trend intensifies for office-based work (Figure A16). The higher drop out of Muslim women from office-based work is consistent with the purdah norm restrictions among Muslim households.

As women eligible for the study were between 18-45 years old and across education levels, we find heterogeneity in job take-up across these demographics. Women with higher levels of education were more likely to start work from both home and office, and this increase in take-up at higher education levels is sharper for home-based jobs. Conversely, a woman's age did not significantly influence her likelihood of office-based job uptake. However, younger women are a lot more likely to work in the job from home (refer to Figure A6). These results are in line with *purdah* norms that are more likely enforced when women are newly married transitioning into their domestic role (Chowdhry, 1993). While the higher engagement of younger women in home-based jobs might suggest a correlation with having younger children, our findings in the Mechanisms section indicate that the presence of young children does not significantly influence job uptake. Hence, home-based jobs seem to engage more women from younger age groups, who may be left out of the labor force with only office-based jobs.

Additionally, our analysis reveals a positive correlation between poorer mental health outcomes and job take-up; a one-unit increase in the tension standardized index corresponds to a 31.9% increase in the odds of a woman starting work, a result consistent across different mental health metrics and supported by our pilot research on marital satisfaction and employment decisions.[38] We do not find noticeable differences in job take-up by women from different castes or with the presence of in-laws in the household. As few women had previous work experience, we do not find significant differences in job take-up by prior work experience.

[38]Due to the sensitive nature and time-consuming aspect of marriage-related questions, we excluded them from the main survey, drawing these conclusions from a pilot conducted with 445 women.

4.4 Husband Experiment Results

Our findings from the Husband Experiment reveal no preference among husbands for working from home as opposed to office, with acceptance rates of 35% and 31% (p-value=0.40), respectively, from Figure 6. This discrepancy between the male and female responses suggests that women's preference for home-based work is likely not due to the nature of the work itself but due to a more gendered reason.

Figure 6: This graph shows the job acceptance rates for husbands for the home and office. These job offers were made to husbands at endline. We see no difference in job take-up rate between the two locations. The error bars represent 95% confidence intervals.

Moreover, husbands exhibited a wage-responsive labor supply, with job acceptance rates doubling when wages increased from low to high levels (illustrated by the blue bars in Figure 7). In stark contrast, women's job acceptance remained consistent across higher wage levels. Further analysis revealed that husbands were more likely to start work as wages rose, particularly at the high wage level. This indicates that men's labor supply is closely tied to monetary incentives. On the contrary, women's labor supply appears to be influenced by additional factors beyond financial compensation. Notably, job acceptance rates between husbands and wives align only at the high wage level. While husbands are much less likely to accept jobs with low or medium wages, women are also willing to accept jobs at these lower wage levels.

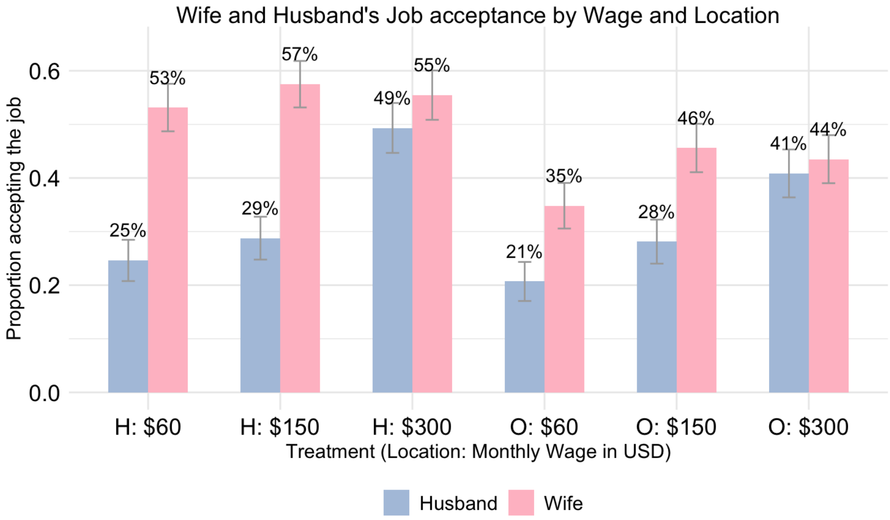

Figure 7: This graph shows the job acceptance rates for husbands and wives for the same job offer (wage level and location). The treatment assignments were to a digital job, either from home (H) or from an office (O) for low ($60), medium ($150), and high ($300) monthly wage levels. These job offers were made to husbands at endline, and they were informed they had some probability of getting the job if they started to work. While we see a monotonic relationship between wage and job take-up rate for husbands, this is not observed for women. Error bars represent 95% confidence intervals.

5 Mechanisms

This study aims to causally estimate how offering digital jobs at home and outside the home influences women's labor supply, demonstrating a substantial increase in workforce entry. We now analyze the reasons behind the sharp difference in job take-up between office and home settings, even when commonly-known practical barriers to employment are mitigated. Known practical barriers include safety and travel costs[39] and labor demand constraints. As we control for these in the design of the experiment, they are unlikely to be playing a key role in explaining the difference in job take-up between the home and office.[40]

We first ask: Which women preferred the home to the office? Are some women likely to experience more barriers to working from an office? To test this, we exploit the heterogeneity in our sample.

5.0.1 Childcare and Other Caregiving Responsibilities

First, we test whether women with young children had more difficulty in starting work from an office than from home. While 91% of our sample had children, half of the full sample had at least one young child below the age of eight. As women are expected to manage the majority of childcare responsibilities, they may be prevented from working outside the home. If the actual burden of childcare was a constraint, women with young children should be less likely to take up jobs from offices. However, we see that the WfO take-up rates are very similar for women with and without

[39] At the time of the full-scale survey conducted from the end of 2022 through 2023, COVID-19 was not a concern for women.

[40] Only 1.5% of women rejected office-based jobs due to safety reasons. Hence, safety and travel costs likely do not explain the gap. Further, the job intervention was designed to keep the timings flexible both from home and office where women could work any number of hours between 10 A.M. to 6 P.M. in a day. Jobs were provided to women at their doorstep, where the team visited each house at least two times and called a third time to provide job details. Women were also provided with a job brochure and a voucher with helpline numbers. Hence, timing flexibility and job search costs or lack of information were not constraints.

young children, as seen in Figure 8. This pattern holds true across various child age groups, ranging from one to eight years old.

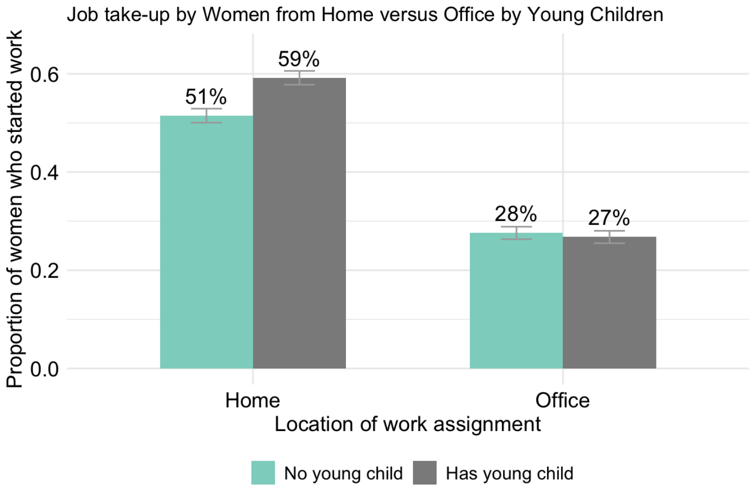

Figure 8: This figure shows the proportion of women who started to work from home and an office by whether or not they had at least one young child below the age of eight. There is only a small difference in take-up between women with and without young children, which does not explain much of the difference in take-up between the two work locations. Error bars show the 95% confidence intervals and standard errors are clustered within strata.

This is likely due to our experimental design that allowed women to bring their children to the offices while they worked;[41] 15% of women assigned to offices brought their children to work. Other women enlisted family members or neighbors to care for their children, with approximately 40% of women who worked at offices doing so.[42] Therefore, the difference in job take-up between home and office does not appear to be explained by the actual burden of childcare, either in terms of time commitment or the need to be constantly present at home with the children.

Furthermore, the presence or absence of elderly care responsibilities does not account for the preference in job take-up from home. We find that 37% of women dedicated a portion of their day to elderly care or other caregiving duties, with an average of 1.7 hours spent daily by those involved in such roles. However, as depicted in Figure A7, there is no marked difference in job take-up between women engaged in elderly caregiving and those who are not.[43] Interestingly, women with caregiving responsibilities show a 20% higher likelihood to opt for office-based work compared to those without such duties, aligning with qualitative feedback indicating that some women find the office a refuge from overwhelming caregiving tasks at home.

Next, we explore if home-based jobs offer other advantages that make office jobs appear less attractive. Two plausible explanations that could make working from home more favorable for these women are (i) *Practical constraints*, such as the ability to multitask with household responsibilities, which focuses on the tangible burdens of childcare and other housework physically constraining women from working outside the home, or (ii) *Domesticity constraints*, which constrain women from leaving home for work, even in the absence of actual housework or childcare responsibilities. To test for these mechanisms, we run a follow-up Mechanism Experiment.

[41] They were informed about this in the survey itself before they made their job decisions.

[42] Additionally, 60% of women stated that even if daycare offices were provided, they would still be unable to engage in paid work due to constraints other than childcare.

[43] These elderly caregiving activities mostly involve taking care of the husband's parents at home.

5.1 Mechanism Experiment Design

To explore why women may prefer WfH, we run a follow-up field experiment at endline where women across all seven arms from baseline (treatment and control) are re-assigned to one of five different job offers.[44] These job offers in the second round are only for a week, but the job tasks are similar. These five job offers include **Work-from-Home (eTreatment 1)** and **Work-from-office (eTreatment 5)**, and three additional offers that add constraints to WfH. The wages offered for these jobs are the same as from baseline so there is no change in wage for the workers. There is no pure control group for this experiment that does not receive job offers.

WfH and No Multitasking: eTreatment 2. In this "housework responsibilities" arm, women are assigned work-from-home jobs with restrictions on multitasking with any other work and mandatory longer, uninterrupted work periods. To ensure compliance, the application features time-sensitive notifications and automatic task expiration for breaks, resulting in potential earnings loss for delayed responses. Women were shown how the notifications would work during the job offer, so they understood the process beforehand. We use this to test for women's actual housework burden.

WfH and Check-In at Office: eTreatments 3–4. In the eTreatment 3 "observability constraints" arm, women work from home, but they are required to check-in at an office daily for two minutes to receive a code that would unlock their application to be able to work on the phone. In the eTreatment 4 arm, women do the same, and in addition, they also need to wear a Work ID lanyard visibly when going to and from the office. A surveyor observed whether women wore the ID visibly. The check-in and the ID can be social signals for women working, even when working from home.

5.2 Mechanism Experiment Results

First, the job take-up from home is similar to the primary experiment job take-up within a few hours of work but is much lower from the office. In this second round of jobs, the difference in take-up between home and office increased to 66%, with an even lower office take-up, likely reflecting women's increased awareness of home-based opportunities and anticipation of future home-based offers. The "WfH + No multitasking" arm reduced WfH-only take-up by 8 pp (p-value=0.005), illustrating that the actual housework burden may explain about 25% of the uptake gap. The two-minute "Check-in" arms reduced job take-up by 12 pp (p-value=0.000), suggesting that observability and mobility constraints may explain 34% of the difference in take-up between home and office. Results from the "Check-in + ID" and "Check-in" arms were similar. This may be because, in practice, we learned that women believed they could conceal the ID under their dupatta, effectively making it the same as a "Check-in" only scenario.[45]

[44]This experiment was rolled out for two-thirds of the sample.

[45]In addition, while some women rejected the ID arm due to increased work observability, a few also viewed it more favorably, regarding it as a symbol of pride and recognition.

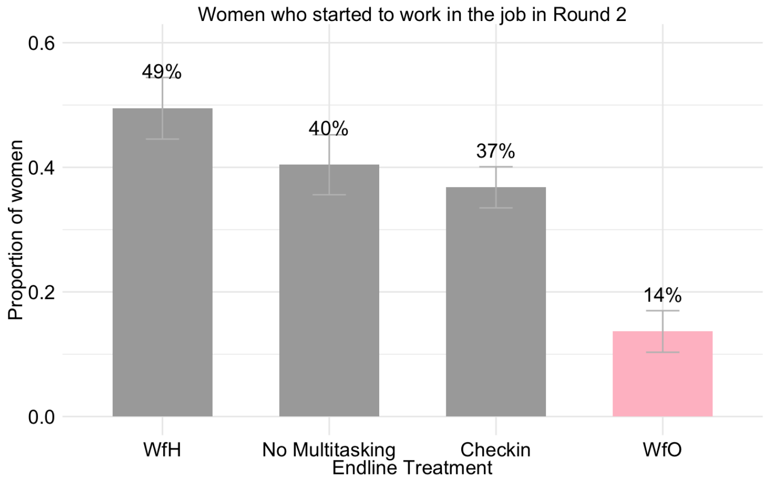

Figure 9: This figure shows the proportion of women who started work from each of the new treatment arms assigned at endline. Adding a Check-in to the WfH arm decreases job take-up by 34% (p-value=0.000). Error bars show 95% confidence intervals and standard errors are clustered within strata.

Taken together, these results suggest that practical barriers and intangible domesticity constraints could account for approximately 59% of the disparity in job take-up between home and office. The residual 41% may stem from other gender-specific preferences for home-based work or *psychosocial pressures* that adhere to domesticity constraints, which may also contribute to the lower acceptance of jobs that disallow multitasking with housework and require check-ins.

5.2.1 Practical Constraints: Housework Responsibilities

The inability to multitask with household chores in office-based jobs accounts for less than one-third of the observed discrepancy between home and office job acceptance. By comparing WfH job take-up rates, with and without the allowance for multitasking, we see that prohibiting multitasking reduces WfH job take-up by 8 pp. This explains approximately 25% of the observed variance in job take-up between home and office settings. If the burden of household chores and the subsequent inability to multitask were the primary factors hindering office job take-up, we would expect a more substantial decline, accounting for a more significant portion of the observed difference.

This result is plausible in our set-up, given the experiment design. We controlled for much of this housework burden as the job is only for two hours per day. From our time-use survey, we find that women's total housework duties (including childcare) took on average six hours per day. Further, as the offices are located very close to home, they could come and go whenever they needed to manage urgent household responsibilities. As the actual burden of housework and childcare leaves around 75% of the difference in home- and office-based job take-up unexplained, we explore other mechanisms, particularly the role of intangible domesticity constraints.

5.2.2 Less Tangible Domesticity Constraints

"Good wives don't do jobs outside home!"

Less tangible domesticity constraints restrict women to the domestic sphere (Papanek, 1973; Evans, 2014). They define women's positions as being at home and fulfilling their roles as dutiful housewives. These constraints may allow women to work, provided the work is home-based. These norms can be enforced both explicitly and implicitly, primarily by husbands or in-laws. Direct enforcement may involve *mobility or observability constraints*, wherein women are restricted from leaving the house for work-related purposes, regardless of the time spent or the distance to work. Implicit enforcement, on the other hand, may manifest as *psychosocial constraints*, wherein the emphasis on being a "good wife" and the perceived responsibilities of housework and childcare can lead women to feel guilty about leaving home for work, even when the actual housework burden may not be constraining (Dhanaraj and Mahambare, 2022; Goldin, 2021). Some husbands, while perhaps well-intentioned, may limit their wives' autonomy under the guise of protecting them. Regardless of the rationale—whether societal or personal—the result is consistent: women are kept at home.

One participant poignantly captured this sentiment: "My husband said I could only work over his dead body. As long as he is alive, I have no reason to work outside [home]."

These constraints may be enforced to prevent *social signaling* of women's work status, reinforcing the husband's status as the primary breadwinner and hers as a "good wife" (Klasen and Pieters, 2015; Bhalla and Kaur, 2011; Pande and Roy, 2021). This preserves his sense of honor and pride within the family and broader community (Goldin, 1994; Bernhardt et al., 2018). In this context, the concept of a "good wife" is multifaceted; she is expected to be the primary caregiver for the family, uphold the family's dignity and honor, remain obedient to her husband's wishes, maintain modesty and chastity, and exercise limited independence, like under the *purdah* (Kantor, 2002). By adhering to these expectations, women are less likely to challenge or threaten their husbands' traditional role as the primary earners. In fact, these norms may be so pervasive that they prevent women from accepting jobs with wages higher than their husbands'. This phenomenon is also known as a *male breadwinner norm* (Bertrand et al., 2015; Pande and Roy, 2021). As a result of these constraints, labor markets for men and women diverge significantly, with domesticity constraints predominantly affecting female labor supply. We first discuss the *mobility or observability constraints* and then the influence of *psychosocial pressures*.

Mobility or Observability Constraints. From the mechanism experiment, we see that a two-minute check-in at a local office accounted for nearly half of the observed discrepancy between home and office job acceptance. By comparing WfH job take-up rates, with and without a Check-in at the center, the added Check-in reduces job take-up by 12 pp or 34%. This highlights the importance of mobility constraints for women's work outside the home.

This mobility or observability restriction is likely enforced due to domesticity constraints and norms. We provide three key insights to substantiate this. First, the lower job take-up with the check-in is observed only for women from less progressive households. As seen in Figure 10, women from less progressive households are 15% less likely to work than women from progressive households in a job that requires a center check-in. To assess households' levels of progressiveness, we used a social norms index from the survey tool where households above the median were classified as more progressive and those at and below the median as less progressive.

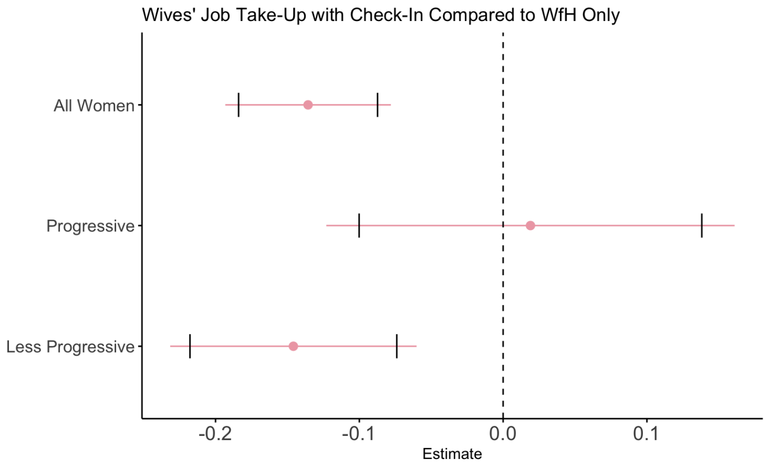

Figure 10: The coefficient plot depicts the impact of offering a WfH with Check-in on job take-up when comparing to the WfH-Only arm. Each point represents the estimated coefficient value for the Check-in group for All Women or women from Progressive or Less Progressive households (higher or lower than the median on a progressiveness index). The bars showcase the 95% confidence intervals, and the black dashes indicate the 90% confidence intervals. "All Women" acts as a baseline group, with "Progressive" and "Less Progressive" groups being compared against it. The results indicate that while the Check-In was less favored than WfH-Only for Less Progressive women, it was about the same for Progressive women. Standard errors are clustered within strata, and regressions include strata-fixed effects.

Second, from the survey with husbands, we find that 52% of husbands would mind if their wives worked outside the home but not at home. Given that the more "progressive" husbands accepted the survey, this statistic is likely to be even lower for other less progressive husbands. Further, only 32% of husbands perceived that even half of the men in their community would think it is right for a woman to work. Hence, there is resistance from husbands due to community or household norms that may restrict women's work, particularly outside the home. Third, most women who rejected the job (more than 40%), particularly from the office, stated the primary reason as *"husband did not allow"*.

Checking in at the office publicly signals women's employment status in the community. From our primary experiment and neighbor interviews, we observed that the employment status of women in the Work-from-Office (WfO) arms was more widely known than those in the Work-from-Home (WfH) arms. This highlights a key distinction: The WfO arms' public nature. Women might hesitate to leave home for work due to social signaling concerns. In the "Check-in with Work ID" (eTreatment 4) arm, the office visit's purpose was made explicit. Although uptake was slightly lower in the ID arm, it was similar to the "Check-in Only arm," as women concealed their Work IDs, reducing its effectiveness as a social signal. The 37% job uptake in the "Check-in" only arm might be inflated; some women avoided office visits by having family members collect codes, effectively treating it as a WfH job. Additionally, women often misled family or neighbors about their destinations, citing errands like market visits or school runs while they were actually going to the office.

Psychosocial Constraints. Women may be restricted through psychosocial constraints emphasizing their behavior as a "good wife." While we do not test for these constraints directly across home or office take-up, as it is difficult to do so in practice, we find some evidence suggesting that women may sometimes act under these psychosocial constraints. In particular, we find some suggestive evidence that wives may behave under a *male breadwinner norm*, particularly when they know their husbands will not be informed about their job offer by the employer. This suggests a belief that a good wife should not out-earn her husband.

To show this, we use results from the primary experiment where 50% husbands were assigned to a husband survey and information treatment. The random assignment of the husband survey in the primary experiment acts as an "external validation" of the job's characteristics rather than an information treatment, as more than 90% of women had already discussed the job details with their husbands before starting work. Despite this, many women chose to withhold wage information from their husbands, although they were concerned about potential repercussions if their husbands discovered this. This scenario potentially limits women's independence in decision-making. Therefore, any effects on job take-up are likely attributable to women's perceptions of how their husbands might react to job details shared solely by them (perceived as less trustworthy) versus details verified by a third party (perceived as more trustworthy). Notably, we observe a non-monotonic relationship between job take-up and wages for both work-from-home (WfH) and work-from-office (WfO) in the absence of a husband survey; women are approximately 8% less likely to accept high-wage jobs compared to medium-wage jobs,[46] as illustrated in Figure 11. This indicates that higher wages may not only fail to boost job take-up but could potentially reduce it if women believe their husbands will remain uninformed by an external, trusted source.

One interpretation of these findings is that external validation from a third party increases women's ability to take higher-wage jobs, possibly because it makes their choices more socially acceptable or justifiable to their husbands. When a husband survey is assigned, women's job choices increase with wages, with take-up increasing by 68% from low to high wages from the office. This suggests that women might underestimate their husbands' willingness to accept a higher-wage job, especially one requiring work outside the home. Indeed, 40% of women express concern about earning more than their husbands, possibly avoiding higher-wage opportunities in the absence of external validation.

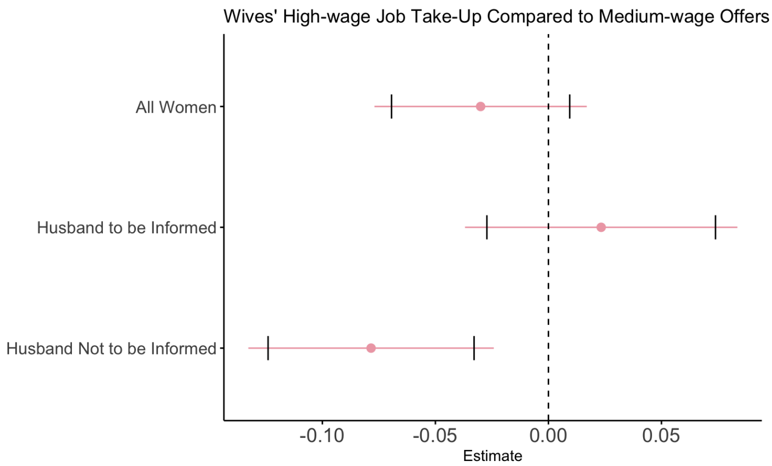

Figure 11: The coefficient plot depicts the impact of offering a high-wage job offer on job take-up when comparing to the medium-wage job offers by whether or not their husbands were to be informed about the job details. Each point represents the estimated coefficient value for (i) all women, and (ii) women whose husbands were assigned to the information treatment, and (iii) women whose husbands were not assigned to the information treatment. The bars showcase the 95% confidence intervals, and the black dashes indicate the 90% confidence intervals. The results indicate that when the husband was not to be informed, women were less likely to accept a high-wage offer (one that possibly doubled their household income) than when the husband was to be informed. Standard errors are clustered within strata, and regressions include strata fixed effects.

Further, husbands and other family members may have a large influence on women's decision making around employment, also contributing to psychosocial constraints. We find some suggestive evidence for this across multiple decision points in the job acceptance process. On Day 1 at baseline, 63% of women accepted the job, but this number dropped to 48% on Day 2 at baseline, and ultimately only 41% commenced work. The most significant reduction in job acceptance occurs between Day 1

[46]This non-monotonic relationship between wages and job take-up was pre-registered in the AEA registry.

and Day 2. Investigating this decline reveals that between these two decision points, the majority of women (86%) discussed the job offer with their husbands. A smaller percentage consulted with their mothers-in-law or fathers-in-law (17%), and even fewer discussed it with neighbors (7%). Therefore, discussions with husbands appear to be a significant driver of the drop from the Day 1 decision to the Day 2 decision, as illustrated in Figure A9. Only 10% of women claimed they made their Day 2 decision without consulting anyone else. By the end of the study, 7% of women disclosed that they had concealed the job from their family members, including their husbands.

For Work-from-Home jobs, the Day 2 decision and Starting Work rates are similar and lower than the Day 1 decision, as seen in Figure A8. However, for Work-from-office jobs, the gap between the Day 1 and Day 2 decisions is much larger, suggesting families may be more restrictive for office-based work than for home-based work. Further, the difference between the Day 2 decision and Starting Work rates is also larger, suggesting women possibly overestimated their ability to work from offices even in their Day 2 decision. However, for women from less progressive households, the largest drop happens at the Day 2 decision stage, which almost accurately predicts whether they start work from the offices.

Qualitative Insights into Domesticity Constraints. While our experimental design seeks to unpack various aspects of domesticity constraints, there remain dimensions that cannot be quantitatively captured. We supplement our analysis with qualitative evidence that illuminates the social and patriarchal pressures deterring women from employment.

Over 40% of women attributed their job rejection primarily to their husbands' disapproval. This aligns with our observations on mobility constraints and social signaling costs. Among women claiming they were not allowed to work, nearly half cited childcare responsibilities, a socially acceptable justification for staying home. A prevalent method for dissuading women from employment is to inflate their domestic duties. One respondent remarked, "My husband tells me that I can work only if I fulfill all my domestic responsibilities first—making meals, taking care of my children, cleaning the house, taking care of my in-laws—tasks without any help from him or my in-laws." This scenario often makes not working a less contentious choice. While husbands predominantly influence this decision, the role of mothers-in-law and other paternal relatives can also be significant. At least 5% of women mentioned their in-laws' objections as a barrier, despite their husbands' approval, and this may be an under-estimate. At least 15% of surveys may have been influenced by the presence of mothers-in-law (8% had mother-in-laws present throughout, others intermittently), and 12% may have been affected by husbands' brief appearances (5% were present for the entire survey), potentially impacting responses about household permissions.[47]

The extent to which husbands permit their wives to work varies significantly by job location, reinforcing that husbands are more concerned about their wives working outside the home than within it. Specifically, 42% of women reported being allowed to work from home. This proportion declines to 28% for jobs elsewhere in their community and reduces to just 18% for jobs outside their community (Figure 12). This pattern is even more pronounced among the Muslim women in our study, with only 18% reporting that they are permitted to work outside their community, as also observed in previous studies (Klasen and Pieters, 2015). These numbers corroborate our earlier findings on gendered preferences for work location.

[47]Surveys where husbands or mother-in-laws were present would not have been possible without their presence due to household restrictions.

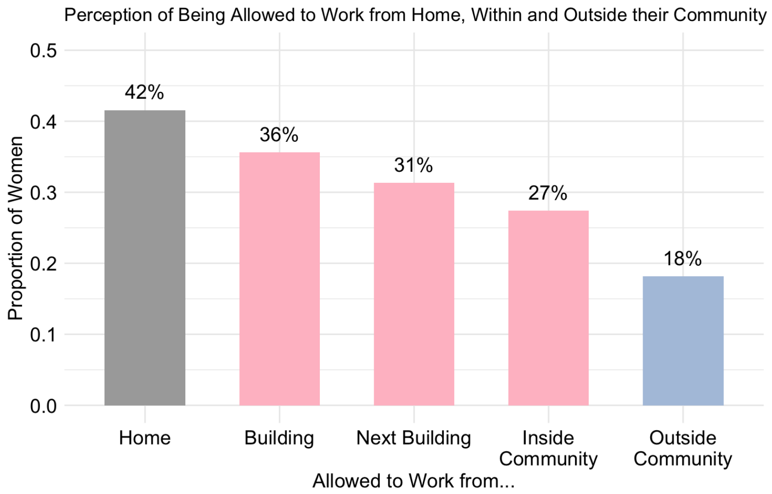

Figure 12: This graph shows the proportion of women allowed to work from each of the locations: home, their own building, a next-door building, inside their own community, and outside their own community but in a neighboring community (outside community). 42% of women are allowed to work from home, but only 18% are allowed to work from outside their own community. These estimates are women's perceptions of whether or not their husbands and in-laws would permit them to work from each of the locations. The orange bar represents allowance from home, the pink bars represent allowance from outside home but from within the community, and the blue bar represents allowance from outside the community.

Further enforcing these norms is the husbands' distrust towards their wives', sometimes escalating to suspicions of infidelity or incompetency in navigating the outside world. In our sample, half of the wives had lived in villages in their native states before relocating to Mumbai only after marriage. Families often prefer to keep women insulated from external influences, thereby avoiding exposure to new ideas. This sentiment extends to mothers-in-law, supporting our findings on social signaling and the role of extended family in shaping women's employment choices.

Some women may also be constrained even from working at home. The 40% who do not even accept a job from home may be constrained by a variety of barriers, including personal constraints like pregnancy and other health issues; unwillingness or lack of desire to work; and gender norms wherein husbands or in-laws forbid them from working, even when the work remains within the family's view. In some families, generations-old traditions dictate that women should not earn an income, leading them to reject even high-wage WfH job offers despite exceeding their husband's monthly earnings. This aligns with our observations on the non-monotonicity in job take-up by wages if the husband survey is not assigned.

6 Discussion and Conclusion

Our results demonstrate the dynamics of married women's labor supply for home-based work, shedding light on the intricate factors that influence their participation in the workforce. Through meticulously designed field experiments, we analyze married women's employment constraints, implementing scalable and real-world job opportunities from both at-home and office settings. These digital remote jobs dramatically increased the labor supply of women traditionally left out of the workforce. However, despite minimizing many practical barriers in the office environment—by offering flexible, part-time jobs in a women-only, child-friendly space located conveniently close to women's homes—only one in four women outside the workforce opted to take up employment in this specially designed nearby office. This suggests that while such interventions can encourage workforce participation, substantial barriers remain. The home-based job option, with double the take-up rate compared to the office, underscores the profound impact of a job's physical location, which is even more important than financial incentives for women's entry. The preference for home is gendered, as husbands did not show a similar home preference in this context and is not driven mainly by childcare or other caregiving responsibilities concerns.

We highlight intangible *domesticity constraints*, which dictate that a woman's place is in the home, as a potential major obstacle—possibly more significant than the actual burden of household chores for such part-time gig work. WfH jobs appear to mitigate the impact of these constraints, allowing housewives to engage in paid labor without transgressing social expectations that traditionally confine them behind the *purdah*. The white-collar designation of these digital jobs may not threaten the husband's perceived role as the primary provider (Goldin, 1994). Furthermore, the invisibility of WfH roles can offer women a pathway to financial independence, as it accords with their families' expectations and definitions of domestic responsibility. These constraints deter women from accepting employment even from gender-specialized offices, highlighting the need for a broader understanding and addressing these societal expectations. In light of these findings, we propose three key considerations to comprehend better and navigate the complexities of women's labor force participation.

First, we highlight the implications of higher wages for job take-up by different types of women. In our context, we distinguish three types of women based on husbands' views: (1) those always allowed to work from home and office (progressive), (2) those never allowed to work even from home (conservative), and (3) those permitted to work from home but not from the office (less progressive). Our study shows that even the difference in wage from high to low was insufficient in getting more women to start working ($240/month). If women are of the type who are forbidden from doing a job, they will not be able to engage in paid work even at a very high wage. Our experiment allows us to bind the amount of constraints women experience at $300 per month. For women from conservative households, the fixed cost of women working is exceptionally high; no reasonable wage could get them to enter the workforce. For women from more progressive households, even the lowest wage is sufficient to get them to enter. Hence, we would need an even lower wage to measure their wage elasticity. The wage range offered in this experiment, while within the market rate for such digital jobs, was on the higher end of the types of jobs available in the setting and often even higher than the husband's salary. Yet, we learned that "breadwinner" husbands usually dismissed women's earnings as inconsequential—merely "pocket money" or a "pastime." Even when women out-earned their husbands, many felt compelled to downplay their financial contributions to preserve family dynamics. In this context, 60% of all expenditure decisions were made by husbands alone, 9% had husbands and wives making joint decisions, 9% had wives making the decision herself, and the rest had other family members making the decisions alongside. Hence, women had much less bargaining power in the household. These stylized facts could help explain why we do not observe a traditional upward-sloping labor supply curve for housewives.

Second, examining gender-specific determinants of labor supply, we show that men and women may value different job features. Men are much more responsive to wages and do not show preferential uptake for either home-based or office-based work. Hence, location and job flexibility appear to have a lesser influence on men. This suggests a nuanced framework in which "What Works for Her" may not necessarily align with the determinants influencing male labor supply. Job designers and employers may need to factor in their specific needs to get women traditionally out of the workforce to join. Notably, younger and more educated women are more inclined to work from home, underscoring the importance of tailoring home-based job opportunities to their specific requirements to facilitate their early entry into the workforce.

Third, our findings suggest that office settings may provide additional non-pecuniary employment benefits (Hussam et al., 2021). Women assigned to offices experienced improved social networks and increased mobility compared to those working from home. For example, 10% of workers assigned to offices joined job-related WhatsApp groups, compared to just 2% of workers assigned home. Additionally, women working from the office reported a more satisfying work experience, and their families and communities were more supportive, both in attitude and practical respects like providing childcare assistance. Notably, women assigned to offices in the primary experiment had a higher likelihood of accepting future office-based employment. Insights from focus group discussions also affirm these advantages of working from local offices. Women not only developed stronger bonds and learned from one another but were more enthusiastic about their jobs (Prillaman, 2023). Many saw the work environment as a respite from home-based stressors and devised collaborative childcare arrangements that did not compromise productivity. Women also felt the office job gave them a new identity, graduating from a "housewife" to an "office-going, working woman." These observations underscore the multiple, albeit less tangible, benefits for women who work from offices. However, such identity shifts associated with office work might contribute to resistance from household members.

Finally, the significant overall increase in job uptake by young women is likely partly due to the digital nature of selected job intervention, which aligns well with the scalable jobs of the future. We piloted both manual and digital jobs from the same home and office settings and found the overall uptake of manual jobs[48] to be 22% with a significant 80% difference between home and office-based jobs. At the same time, the uptake for digital jobs was more than 50% with a much smaller difference between home and office. Hence, digital gig work provides new opportunities for women to work, especially for populations currently left out. Specifically, in an urban Indian setting where merely 20% of married women are in the labor force, such flexible, smartphone-based digital work could be feasibly implemented with significant expected increases in female labor force participation. This shifts the narrative from a labor supply-constrained problem to a labor demand one—with millions more women able to enter the workforce with digital gig work, what jobs are available for them to do?

From a Government perspective, digital work could serve as an alternative social protection program for urban women to traditional schemes like the Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA), which has effectively increased women's employment in agriculture (Desai, 2018). Our study only provides evidence for *short-term* jobs and their implications for women's workforce entry. Longer-term, permanent employment may have different determinants for entry and retention. Our study informs labor policy by demonstrating that both Work-from-Home and Work-from-Office jobs have the potential to increase female labor force participation beyond existing traditional jobs. Given the rising prevalence of remote work and apparent gender differences in labor outcomes, these insights have broad implications beyond the Indian context; for instance,

[48] This manual work involved decorating bangles that came in boxes of dozens for a partner organization that ran a bangles business in Govandi slums in Mumbai and were looking to hire more women. Payment for home and office offers were similar to the digital jobs. For WfH, these boxes would be delivered home and picked up from home, and for WfO, the bangle decoration would happen at a local office.

digital remote work may offer a crucial lifeline in countries like Afghanistan, where women are legally confined to their homes. Policymakers could thus leverage this data to create targeted employment opportunities for women, either through digital work-from-home initiatives or local offices, to better align with their unique constraints and preferences. However, for them to be promoted, gig work must be accompanied by relevant social security benefits.

This study sheds light on crucial factors influencing women's entry into the workforce, notably the preference for home-based work and the enduring constraints of domesticity. Our findings prompt further exploration into how longer-term employment and various non-financial factors affect women's labor participation. Future research could explore the implications of more permanent job opportunities on household dynamics, particularly between husbands and wives. Additionally, as women transition to working outside the home and rebrand from "housewives" to "working women," it becomes crucial to examine the significance of this change in identity. How do title, respect, and recognition shifts contribute to women's willingness to work and the household's willingness to relieve them of domesticity constraints? Understanding these dimensions will be pivotal in shaping policies and initiatives to enhance women's participation in the labor force.

References

Acemoglu, Daron, David Autor, and Simon Johnson, "Can we Have Pro-Worker AI?," 2023.

Afridi, Farzana, Taryn Dinkelman, and Kanika Mahajan, "Why are Fewer Married Women Joining the Work Force in Rural India? A Decomposition Analysis Over Two Decades," *Journal of Population Economics*, 2018, *31*, 783–818.

Aksoy, Cevat Giray, Jose Maria Barrero, Nicholas Bloom, Steven J Davis, Mathias Dolls, and Pablo Zarate, "Time savings when working from home," Technical Report, National Bureau of Economic Research 2023.

Alam, Muneeza Mehmood, Maureen Cropper, Matias Herrera Dappe, and Palak Suri, "Closing the Gap: Gender, Transport, and Employment in Mumbai," Technical Report Policy Note 2021, World Bank 2021.

Asadullah, M Niaz and Zaki Wahhaj, "Missing from the market: purdah norm and women's paid work participation in Bangladesh," 2017.

Ashraf, Nava, Erica Field, Alessandra Voena, and Roberta Ziparo, "Gendered Spheres of Learning and Household Decision Making over Fertility," Technical Report, Working Paper, 28220 2022.

Atkin, David, Antoinette Schoar, and Sumit Shinde, "Working from Home, Worker Sorting and Development," Technical Report, National Bureau of Economic Research 2023.

Autor, David H, David A Mindell, and Elisabeth B Reynolds, "The work of the future: building better jobs in an age of intelligent machines," 2020. MIT task force on the work of the future.

Bernhardt, Arielle, Erica Field, Rohini Pande, Natalia Rigol, Simone Schaner, and Charity Troyer-Moore, "Male social status and women's work," in "AEA Papers and Proceedings," Vol. 108 2018, pp. 363–67.

Bertrand, Marianne, Emir Kamenica, and Jessica Pan, "Gender identity and relative income within households," *The Quarterly Journal of Economics*, 2015, *130* (2), 571–614.

Bhalla, Surjit and Ravinder Kaur, "Labour force participation of women in India: Some facts, some queries," Technical Report, London School of Economics 2011.

Blau, Francine D and Lawrence M Kahn, "Changes in the labor supply behavior of married women: 1980–2000," *Journal of Labor Economics*, 2007, *25* (3), 393–438.

Bloom, Nicholas, James Liang, John Roberts, and Zhichun Jenny Ying, "Does working from home work? Evidence from a Chinese experiment," *The Quarterly Journal of Economics*, 2015, *130* (1), 165–218.

_ , Ruobing Han, and James Liang, "How hybrid working from home works out," Technical Report, National Bureau of Economic Research 2022.

Buolamwini, Joy and Timnit Gebru, "Gender Shades: Intersectional Accuracy Disparities in Commercial Gender Classification," *Proceedings of the Machine Learning Research*, 2019.

Bursztyn, Leonardo, Alessandra L. González, and David Yanagizawa-Drott, "Misperceived social norms: Women working outside the home in Saudi Arabia," *American Economic Review*, 2020, *110* (10), 2997–3029.

_ , Alexander W. Cappelen, Bertil Tungodden, Alessandra Voena, and David H. Yanagizawa-Drott, "How Are Gender Norms Perceived?," Technical Report, National Bureau of Economic Research 2023.

Chakraborty, Shiney, "COVID-19 and women informal sector workers in India," *Economic & Political Weekly*, 2020, *55* (35), 17.

Chaudhary, Ruchika et al., "India's Emerging Gig Economy: Shaping the Future of Work for Women," 2021.

Cheema, Ali, Asim I Khwaja, Farooq Naseer, and Jacob N Shapiro, "Glass Walls: Experimental Evidence on Access Constraints Faced by Women," Technical Report, Mimeo, Harvard University 2019.

Choudhury, Prithwiraj, Cirrus Foroughi, and Barbara Larson, "Work-from-anywhere: The productivity effects of geographic flexibility," *Strategic Management Journal*, 2021, *42* (4), 655–683.

Chowdhry, Prem, "Persistence of a custom: Cultural centrality of ghunghat," *Social Scientist*, 1993, pp. 91–112.

Datta, Namita, Chen Rong, Sunamika Singh, Clara Stinshoff, Nadina Iacob, Natnael Simachew Nigatu, Mpumelelo Nxumalo, and Luka Klimaviciute, "Working Without Borders: The Promise and Peril of Online Gig Work," 2023.

Desai, Sonalde, "Do public works programs increase women's economic empowerment?: evidence from rural India," 2018. Available at SSRN 3262774.

Dhanaraj, Sowmya and Vidya Mahambare, "Male backlash and female guilt: women's employment and intimate Partner Violence in Urban India," *Feminist Economics*, 2022, *28* (1), 170–198.

Dhar, Diva, Tarun Jain, and Seema Jayachandran, "Reshaping adolescents' gender attitudes: Evidence from a school-based experiment in India," *American economic review*, 2022, *112* (3), 899–927.

Difallah, Djellel, Elena Filatova, and Panos Ipeirotis, "Demographics and dynamics of mechanical turk workers," in "Proceedings of the eleventh ACM international conference on web search and data mining" 2018, pp. 135–143.

Emanuel, Natalia and Emma Harrington, "Working Remotely? Selection, Treatment, and the Market for Remote Work," *FRB of New York Staff Report*, June 2023, (1061).

Evans, Alice, "'Women can do what men can do': the causes and consequences of growing flexibility in gender divisions of labour in Kitwe, Zambia," *Journal of Southern African Studies*, 2014, *40* (5), 981–998.

Fernandez, Raquel, "Women, work, and culture," *Journal of the European Economic Association*, 2007, *5* (2-3), 305–332.

Field, Erica, Rohini Pande, Natalia Rigol, Simone Schaner, and Charity Troyer Moore, "On Her Own Account: How Strengthening Women's Financial Control Impacts Labor Supply and Gender Norms," *American Economic Review*, 2021, *111* (7), 2342–2375.

Fletcher, Erin, Rohini Pande, and Charity Maria Troyer Moore, "Women and work in India: Descriptive evidence and a review of potential policies," Working Paper, HKS Working Paper No. RWP18-004 2017.

Ghai, Surbhi, "The anomaly of women's work and education in India," Technical Report, Working Paper 2018.

Gibbs, Michael, Friederike Mengel, and Christoph Siemroth, "Work from home & productivity: Evidence from personnel & analytics data on IT professionals," Working Paper 2021-56, University of Chicago, Becker Friedman Institute for Economics 2021.

Goel, Rahul, "Gender gap in mobility outside home in urban India," *Travel Behaviour and Society*, 2023, *32*, 100559.

Goldin, Claudia, "The U-shaped female labor force function in economic development and economic history," 1994.

_ , *Career and family: Women's century-long journey toward equity*, Princeton University Press, 2021.

Greenwood, Jeremy, *Evolving Households: The Imprint of Technology on Life*, MIT Press, 2019.

_ , Nezih Guner, and Ricardo Marto, "The Great Transition: Kuznets Facts for Family-Economists," in "Handbook of the Economics of the Family," Vol. 1, Elsevier, 2023, pp. 389–441.

Gupta, Aakar, William Thies, Edward Cutrell, and Ravin Balakrishnan, "mClerk: enabling mobile crowdsourcing in developing regions," in "Proceedings of the SIGCHI Conference on Human Factors in Computing Systems" ACM 2012, pp. 1843–1852.

Gutheim, Philipp and Prayag Narula, "MobileWorks: A Crowd Platform That Works (Against Poverty)," 2012.

Hale, Sylvia M, "Frogs in a Well. Indian Women in Purdah.," 1980.

Hsu, Yen-Chia, Himanshu Verma, Andrea Mauri, Illah Nourbakhsh, Alessandro Bozzon et al., "Empowering local communities using artificial intelligence," *Patterns*, 2022, *3* (3).

Hussam, Reshmaan N, Erin M Kelley, Gregory V Lane, and Fatima T Zahra, "The psychosocial value of employment," Working Paper w28738, National Bureau of Economic Research 2021.

ILO, ""ILOSTAT" database," https://ilostat.ilo.org/data/ 2020. Accessed: 2020-09-08.

ILO, "Smartphones and the Digital Gig Economy: A Gender Perspective," *ILO Policy Brief*, 2021.

Jayachandran, Seema, "The roots of gender inequality in developing countries," *economics*, 2015, *7* (1), 63–88.

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

Jensen, Robert, "Do labor market opportunities affect young women's work and family decisions? Experimental evidence from India," *The Quarterly Journal of Economics*, 2012, *127* (2), 753–792.

Joyce, Simon, Denis Neumann, Vera Trappmann, and Charles Umney, "A global struggle: worker protest in the platform economy," *ETUI Research Paper-Policy Brief*, 2020, *2.*

Kanjilal-Bhaduri, Sanghamitra and Francesco Pastore, "Returns to Education and Female Work Force Participation Nexus: Evidence from India," Technical Report, GLO Discussion Paper 2018.

Kantor, Paula, "Female mobility in India: the influence of seclusion norms on economic outcomes," *International Development Planning Review*, 2002, *24* (2), 145–160.

Kapsos, Steven, Evangelia Bourmpoula, and Andrea Silberman, "Why is Female Labour Force Participation Declining so Sharply in India?," Technical Report, International Labour Organization 2014.

Khanna, Shashank, Aishwarya Ratan, James Davis, and William Thies, "Evaluating and improving the usability of Mechanical Turk for low-income workers in India," in "Proceedings of the first ACM symposium on computing for development" ACM 2010, pp. 1–10.

Kitagawa, Ritsu, Sachiko Kuroda, Hiroko Okudaira, and Hideo Owan, "Working from home: Its effects on productivity and mental health," *Covid Economics*, 2021, *74*, 142–171.

Klasen, Stephan and Janneke Pieters, "What explains the stagnation of female labor force participation in urban India?," *The World Bank Economic Review*, 2015, *29* (3), 449–478.

Krishnan, D, "As India advances, women's workforce participation plummets," *Strategy+ Business by PWC*, 2020.

Kuek, Siou Chew, Cecilia Paradi-Guilford, Toks Fayomi, Saori Imaizumi, Panos Ipeirotis, Patricia Pina, and Manpreet Singh, "The Global Opportunity in Online Outsourcing," 2015.

Kulkarni, Anand, Philipp Gutheim, Prayag Narula, David Rolnitzky, Tapan Parikh, and Björn Hartmann, "MobileWorks: Designing for quality in a managed crowdsourcing architecture," *IEEE Internet Computing*, 2012, *16* (5), 28–35.

Kumar, Anil and Che-Yuan Liang, “Declining female labor supply elasticities in the United States and implications for tax policy: Evidence from panel data,” *National Tax Journal*, 2016, *69* (3), 481–516.

Larrazabal, Agostina J, Nicolás Nieto, Victoria Peterson, Diego H Milone, and Enzo Ferrante, “Gender imbalance in medical imaging datasets produces biased classifiers for computer-aided diagnosis,” *Proceedings of the National Academy of Sciences*, 2020, *117* (23), 12592–12594.

Litman, Leib, Jonathan Robinson, Zohn Rosen, Cheskie Rosenzweig, Joshua Waxman, and Lisa M Bates, “The persistence of pay inequality: The gender pay gap in an anonymous online labor market,” *PloS one*, 2020, *15* (2), e0229383.

Lundberg, Shelly and Robert A Pollak, “Separate spheres bargaining and the marriage market,” *Journal of Political Economy*, 1993, *101* (6), 988–1010.

Malathy, R, “Labor supply behavior of married women in urban India,” Technical Report, Discussion Papers. 593. 1989. https://elischolar.library.yale.edu/egcenter-discussion-paper-series/593.

Mandelbaum, David G, “Sex roles and gender relations in North India,” *Economic and political weekly*, 1986, pp. 1999–2004.

McClelland, Robert, Shannon Mok, and Kevin Pierce, “Labor Force Participation Elasticities of Women and Secondary Earners within Married Couples,” 2014.

McKelway, Madeline, “Women’s employment in India: Intra-household and intra-personal constraints,” Technical Report, Working Paper 2020.

Minturn, Leigh, *Sita’s daughters: Coming out of purdah: The Rajput women of Khalapur revisited*, Vol. 10, Oxford University Press, USA, 1993.

NASSCOM, “Data Annotation and Labelling Services: India Value Proposition and Industry Maturity,” 2023.

OECD Gender Statistics, “Institutions and Development Database,” 2014.

Olivetti, Claudia and Barbara Petrongolo, “Unequal pay or unequal employment? A cross-country analysis of gender gaps,” *Journal of Labor Economics*, 2008, *26* (4), 621–654.

Pande, Rohini and Helena Roy, "“If You Compete with Us, We Shan’t Marry You”: The (Mary Paley and) Alfred Marshall Lecture,” *Journal of the European Economic Association*, 2021, *19* (6), 2992–3024.

Pandey, Divya and Madhulika Khanna, “The Role of Mothers-in-Law in Determining Women’s Work: Evidence from India,” 2023.

Papanek, Hanna, “Purdah: Separate worlds and symbolic shelter,” *Comparative studies in society and history*, 1973, *15* (3), 289–325.

Peters, H Elizabeth, Yasemin Irvin-Erickson, Shirley Adelstein, Ammar A Malik, Teresa Derrick-Mills, Alberto Valido, and Dorothy Esplage, "Qualitative evidence on barriers to and facilitators of women's participation in higher or growing productivity and male-dominated labour market sectors in low-and middle-income countries," 2019.

Phuleria, Harish C, Abhay Anand, and Tajdar M Gulam, "Assessment of indoor and outdoor PM2. 5 in slums of Mumbai, India," in "ISEE Conference Abstracts," Vol. 29 International Society for Environmental Epidemiology 2017, p. 877.

Prillaman, Soledad Artiz, "Strength in numbers: how women's groups close India's political gender gap," *American Journal of Political Science*, 2023, *67* (2), 390–410.

Qin, Duo, Sophie Van Huellen, and Qing-Chao Wang, "How credible are shrinking wage elasticities of married women labour supply?," *Econometrics*, 2015, *4* (1), 1.

Rajpurkar, Pranav and Kaylie Chen, "Assessment of the Accuracy and Bias of a Deep Learning Model for the Detection of Cardiovascular Disease in Chest Radiographs," *Nature Medicine*, 2020.

Rambarran, Richard, "The Socio-Economic Status of Women in the Urban Slums of India," 2014.

Said, Farah, Mahreen Mahmud, Giovanna d'Adda, and Azam Chaudhry, "Home-bias among female entrepreneurs: experimental evidence on preferences from Pakistan," 2019.

Sharma, Neha and Ritu Sindhwani, "How Smartphones Can Help Women Overcome Gender Stereotypes and Biases in the Digital Gig Economy," *Information Systems Frontiers*, 2022.

Sinha, Sharmistha, "Gender digital divide in India: Impacting women's participation in the labour market," *Reflecting on India's Development: Employment, Skill and Health*, 2018, pp. 293–310.

Subramanian, Nivedhitha, "Workplace attributes and women's labor supply decisions: Evidence from a randomized experiment," Technical Report, mimeo 2019.

Sudarshan, Ratna M and Shrayana Bhattacharya, "Through the magnifying glass: Women's work and labour force participation in urban Delhi," *Economic and Political Weekly*, 2009, pp. 59–66.

Suresh, Harini and John Guttag, "A framework for understanding sources of harm throughout the machine learning life cycle," in "Equity and access in algorithms, mechanisms, and optimization" 2021, pp. 1–9.

Tauchmann, Harald, "Lee (2009) treatment-effect bounds for nonrandom sample selection," *The Stata Journal*, 2014, *14* (4), 884–894.

UNDP, "Human Development Report 2010: The Real Wealth of Nations: Pathways to Human Development," 2010.

World Bank, "South Asia Development Update: Toward Faster, Cleaner Growth," 2023.

Figures and Tables

Tables

Table 2: Balance Table

	(1) Control		(2) Treatment		(1)-(2) Pairwise t-test	
Variable	N	Mean/(SE)	N	Mean/(SE)	N	P-value
Age	459	32.73 (0.30)	2859	32.54 (0.11)	3318	0.54
Family size	459	5.01 (0.10)	2859	4.99 (0.04)	3318	0.98
House ownership (=1)	335	0.56 (0.03)	2074	0.57 (0.01)	2409	0.57
Open caste (=1)	335	0.50 (0.03)	2052	0.49 (0.01)	2387	0.97
Husband monthly income (INR)	458	20719.87 (690.82)	2858	19892.60 (265.62)	3316	0.30
Has child below 8 (=1)	459	0.53 (0.02)	2859	0.55 (0.01)	3318	0.43
Hindu (=1)	459	0.53 (0.02)	2859	0.53 (0.01)	3318	0.54
Highest education attained	459	11.07 (0.15)	2859	11.01 (0.06)	3318	0.97
In-laws living in HH (=1)	459	0.41 (0.02)	2859	0.41 (0.01)	3318	0.76
Aspirational monthly income (INR)	459	42511.98 (2590.73)	2859	44684.00 (3618.61)	3318	0.80
Allowed to work (=1)	445	0.69 (0.02)	2751	0.72 (0.01)	3196	0.27
PHQ-8	459	4.33 (0.21)	2859	4.39 (0.08)	3318	0.74
Tension	355	22.27 (0.55)	2136	22.38 (0.22)	2491	0.83

Notes: This table shows the balance table comparing the control and treatment means. The pairwise t-test shows that the groups are balanced on baseline characteristics such as age, family size, house ownership, caste, husband income, children, religion, education level, presence of in-laws, aspirational income, allowed to work status, and mental health status as measured by PHQ-8 standardized index and tension levels (on a score between 0 to 40). Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Intensive Margin Results

Table 3: Intensive margin results across baseline treatment arms

	Minutes (1)	Pay (INR) (2)	Tasks (3)	Productivity (4)	Accuracy (Speech) (5)
Home	126.238	−929.053	−758.895	−0.478***	−0.034
	(209.580)	(818.407)	(684.474)	(0.120)	(0.052)
Low wage	−1075.631***	−10922.600***	−4171.302***	−0.391**	−0.019
	(233.993)	(678.511)	(815.763)	(0.158)	(0.063)
Home x Low wage	−61.316	997.399	446.137	0.149	0.011
	(299.218)	(849.386)	(1002.410)	(0.186)	(0.076)
Med wage	−41.197	−6481.091***	−473.441	−0.186	0.066
	(222.694)	(733.708)	(772.408)	(0.137)	(0.056)
Home x Med wage	−319.174	5.078	−804.733	0.006	−0.061
	(293.066)	(923.034)	(976.107)	(0.162)	(0.070)
Constant	2294.302***	10294.868***	8447.215***	3.209***	0.663***
	(421.691)	(1262.037)	(1361.884)	(0.232)	(0.094)
Observations	1186	1187	1186	1186	841

Notes: This table shows the results on the intensive margin, that is, the effect of working from home at low and medium wages, and their interactions compared with working from the office at a high wage level. Women working from home and those in lower wages have lower productivity. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix A: Additional Figures and Tables

Figures

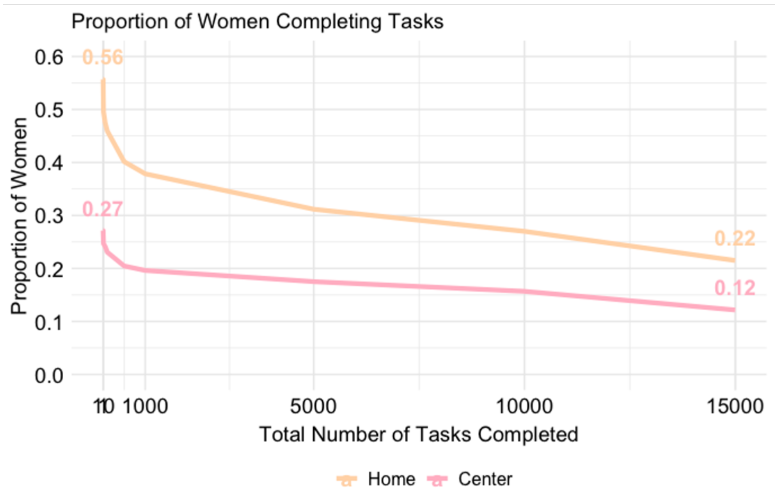

Figure A1: This graph shows the proportion of women who completed the job from the start of work (> 0 tasks) to all the tasks (15,000) from home and office.

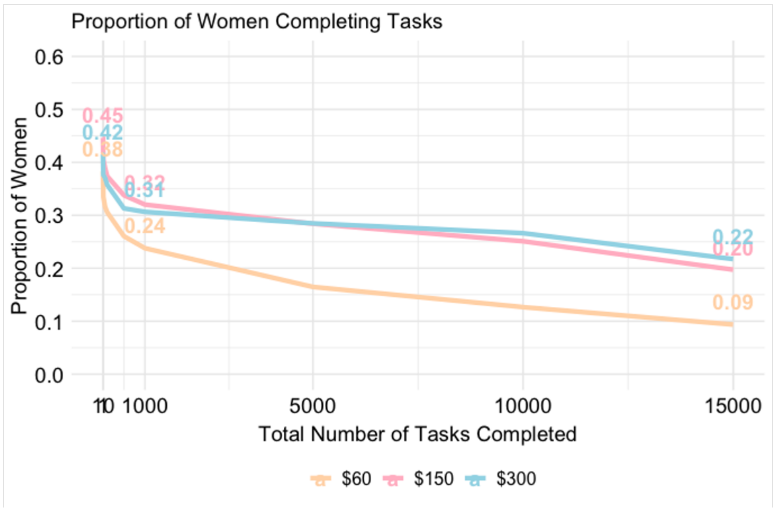

Figure A2: This graph shows the proportion of women who completed the job from the start of work (> 0 tasks) to all the tasks (15,000) at the three offered wages.

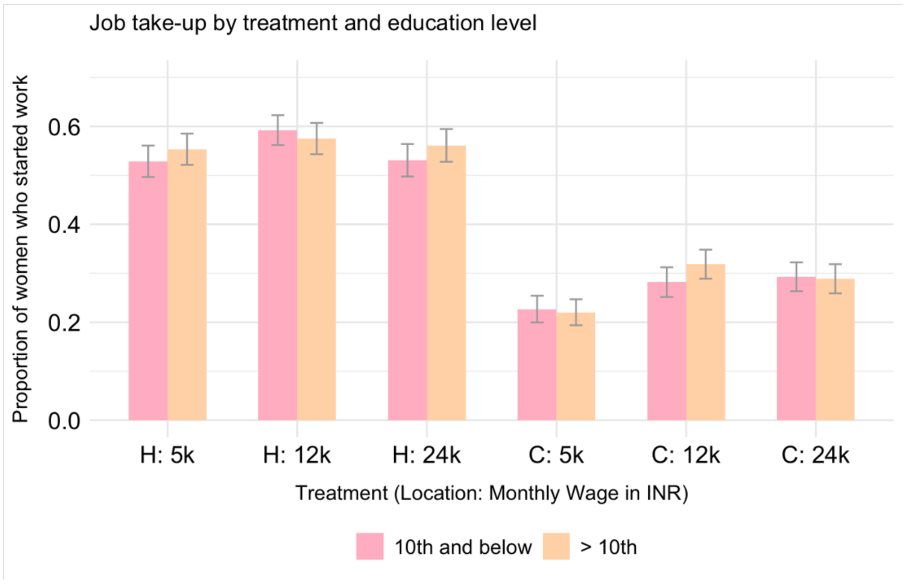

Figure A3: This graph shows the difference in proportion of women starting work when they are randomly assigned to one of six treatment arms by education level (completed 10th grade or below, or above 10th grade). The treatment assignments were to a digital job either from (H) or from local offices (C) for low (5k INR), medium (12k INR), and high (24k INR) monthly wage levels. There is no statistically significant difference in job take-up for women at different education levels. Error bars represent the standard errors. The orange bars represent women with education level greater than 10th grade and the pink bars represent women with education level 10th grade or below. Error bars represent the standard errors.

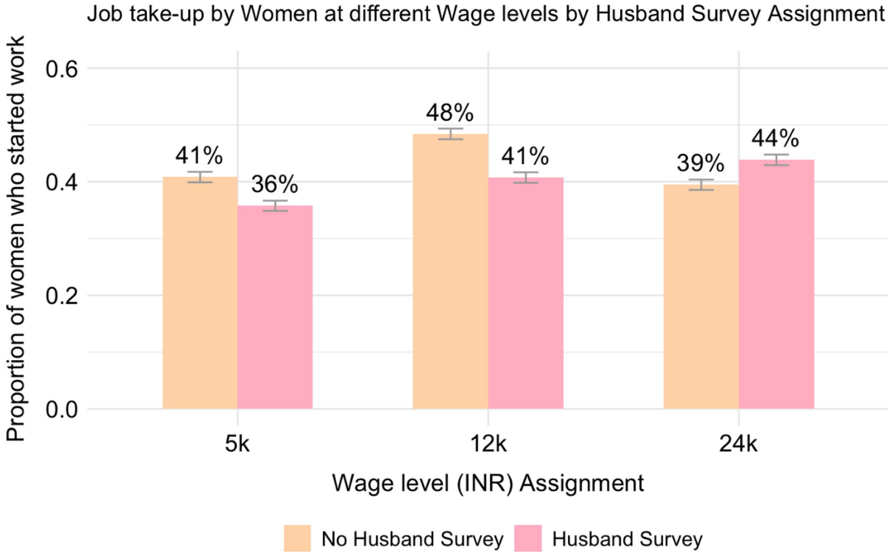

Figure A4: This graph show the proportion of women who started work for each of the three wage levels by whether or not a husband survey was assigned. The treatment assignments were to a digital job either at low (5k INR), medium (12k INR), or high (24k INR) monthly wage levels. Women were informed whether their husbands were going to be surveyed before they made their decision to start working in the job. We see a non-monotonic relationship in job take-up by wage when there is no husband survey. Error bars represent the standard errors.

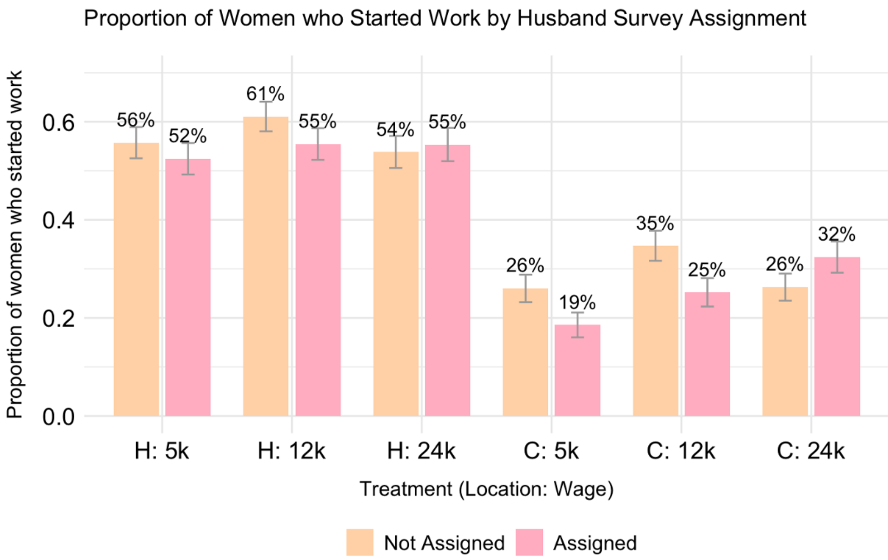

Figure A5: This graph show the proportion of women who started work for each of the six treatment arms by whether or not a husband survey was assigned. The treatment assignments were to a digital job either from (H) or from local offices (C) for low (5k INR), medium (12k INR), and high (24k INR) monthly wage levels. Women were informed whether their husbands were going to be surveyed before they made their decision to start working in the job. We see a non-monotonic relationship in job take-up when there is no husband survey. Error bars represent the standard errors.

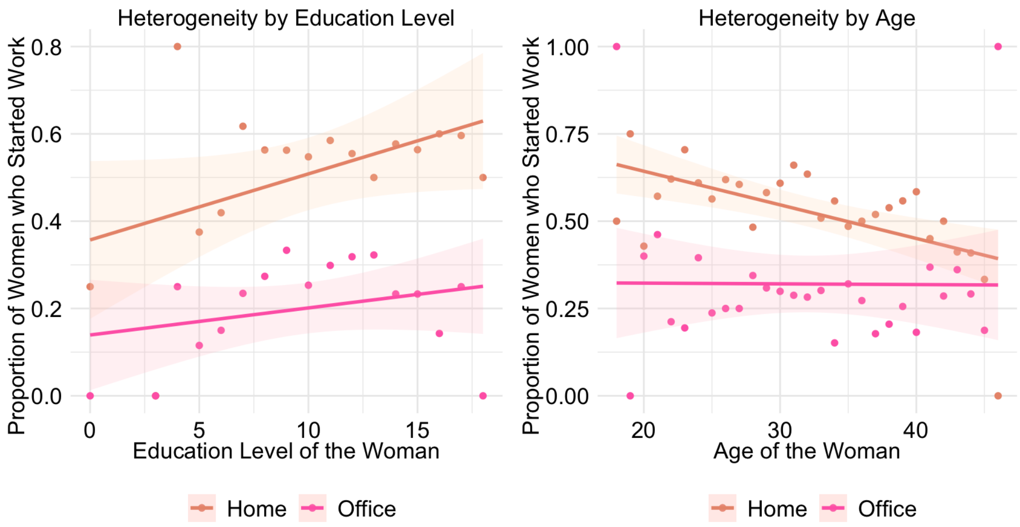

Figure A6: These scatter plots show the proportion of women who started work from Home and Office by education level and by age. More educated women are more likely to take up the job from both home and office, but particularly so from home. From the right panel, we find that younger women mainly drive the difference in job take-up from home and office. The intervals around the fitted lines represent the 95% confidence intervals.

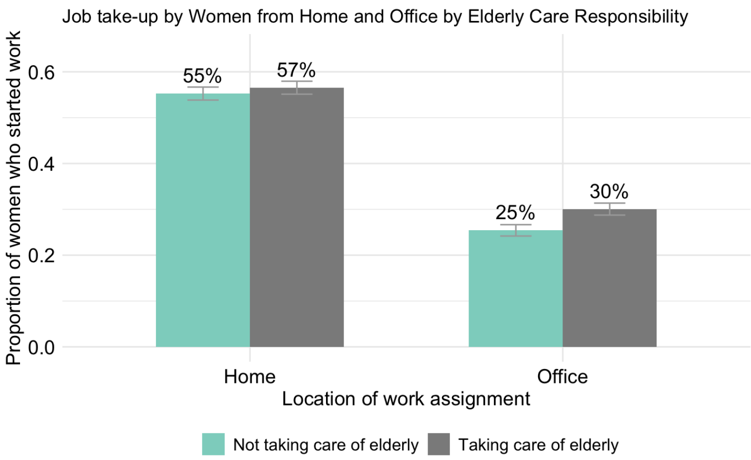

Figure A7: This figure shows the proportion of women who started work from Home and Office by whether not they were performing elderly care responsibilities. We do not see much difference in take-up by elderly care. Error bars show the 95% confidence intervals, and standard errors are clustered within strata.

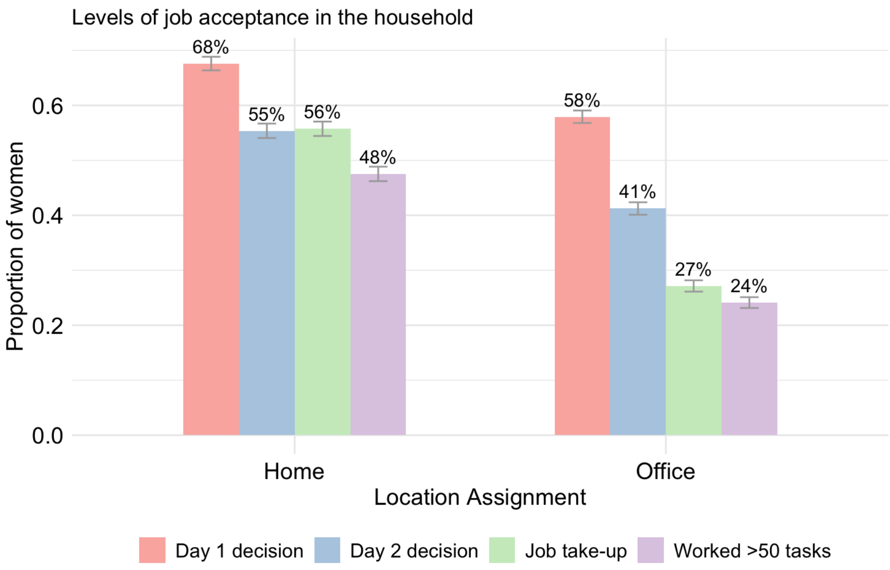

Figure A8: This graph shows the decision-making on job acceptance from home or office in the household to shed some light on women's own preferences along with household influences. The Baseline survey was conducted over two days. The job offers were provided on the first day, and women were then asked for their own decision on whether or not they accepted the job (Day 1 decision). The surveyors then went back to confirm with the women the next day on their job decision (Day 2 decision). Most women had spoken to other family members before making their Day 2 decision. Whether or not women actually started to work is characterized by "Job take-up" in the third bar, and if they continued working for 1-2 hours, marked as "Worked>50 tasks" in the fourth bar for each job location assignment. There is a sharper decline with each subsequent job decision (Day 1 to Day 2 to actually working) for women assigned to offices. Error bars represent standard errors.

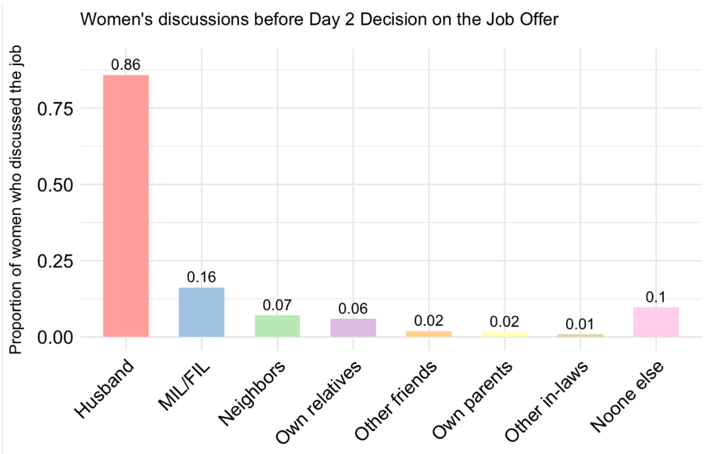

Figure A9: This graph shows the proportion of women who had discussions with their husband, mother-in-law or father-in-law, neighbors, parents, and other relatives between the Day 1 and Day 2 baseline surveys. Women were asked who they discussed the job offer with in the Day 2 survey. 86% of women had discussed the job with their husbands.

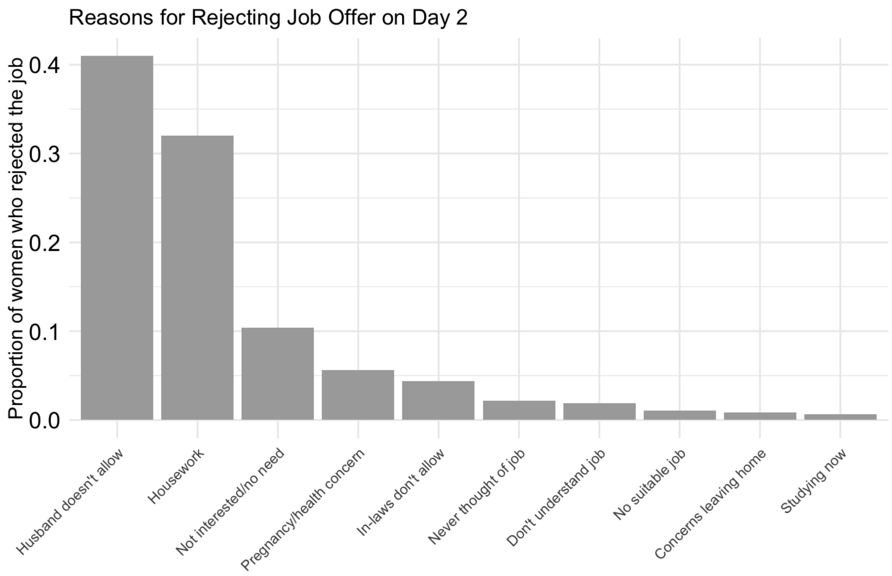

Figure A10: This graph shows the proportion of women who state various reasons for rejecting the job offer in the baseline survey (Day 2 survey). This question captures their main reason for rejection, so we record only one response per woman as the reason. Most women stated "husband does not allow" as the main reason, followed by "household chores/childcare". Since we establish that household chores and childcare were not actual constraints for this work, this reason may be an extension of the norms of domesticity that keep women home.

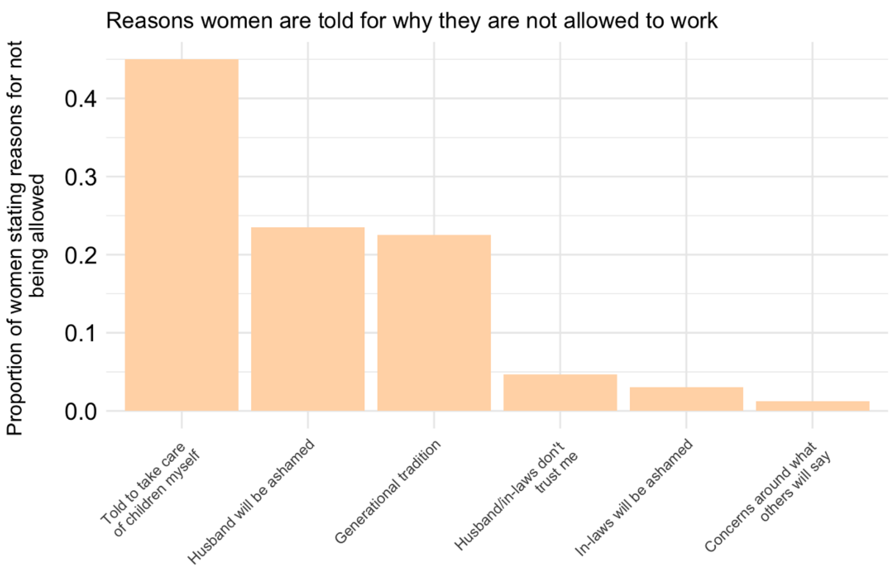

Figure A11: This graph shows the results only for women who stated their main reason for job rejection as "husband does not allow". It shows the proportion of such women who state various reasons for husbands not allowing them to work in the baseline survey (Day 2 survey). Most women think they are not allowed to work since they need to "take care of children myself [themselves]", followed by husband being ashamed of the woman doing a job or following a generational tradition of women not doing any paid work.

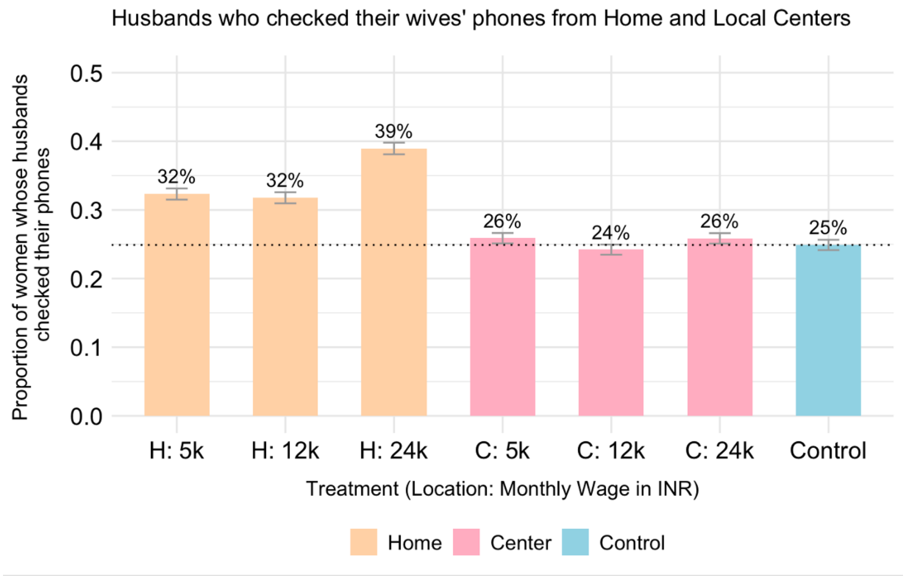

Figure A12: This graph shows phone check-in rates by husbands. Husbands may help women from home in the job, but that's in 5% of cases overall and not different by wage. Error bars represent standard errors.

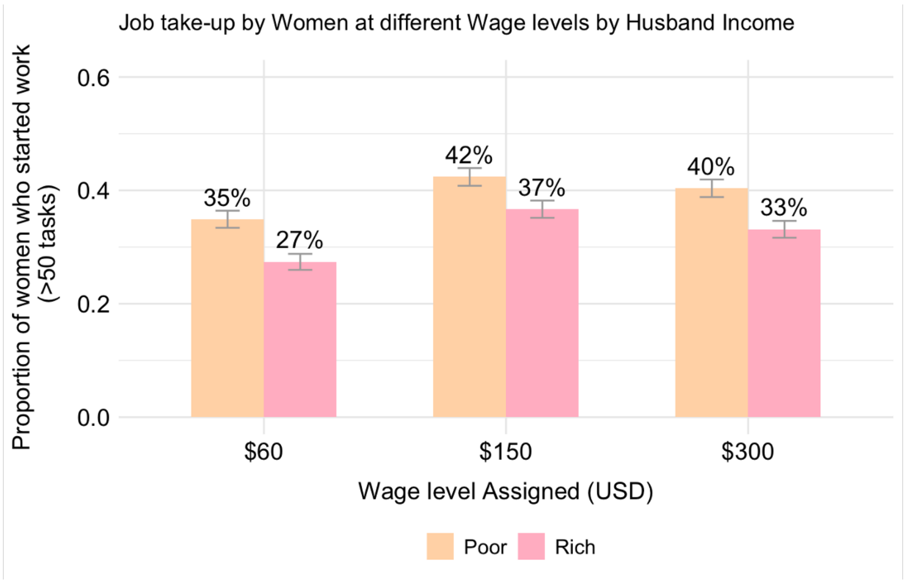

Figure A13: This graph shows the job take-up rates by wives across the three wage levels for husbands who are "rich" (earn more than the median wage), or "poor" (earn less than the median wage). Error bars represent standard errors.

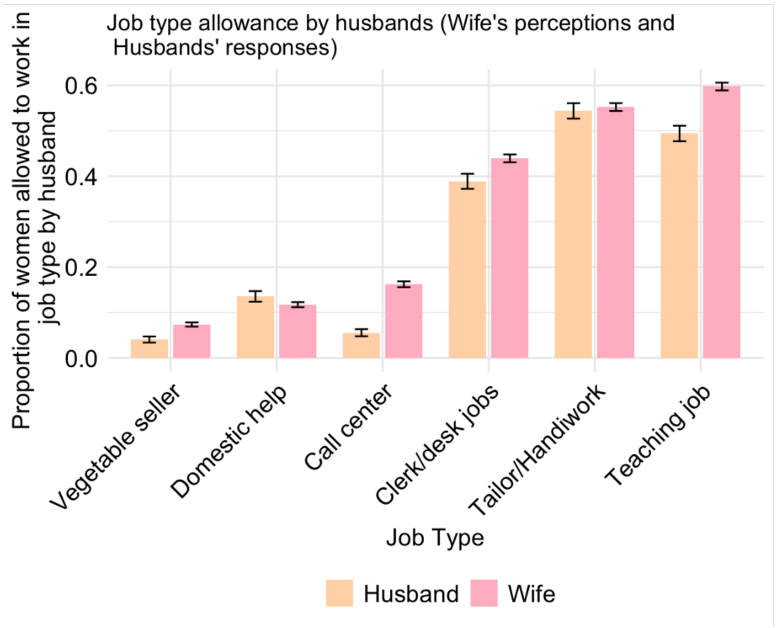

Figure A14: This graph shows the job types where husbands would "allow" their wives to work. Women stated their preferences on husbands' responses and husbands stated their own preferences. These were job preferences collected at Baseline. Error bars represent standard errors.

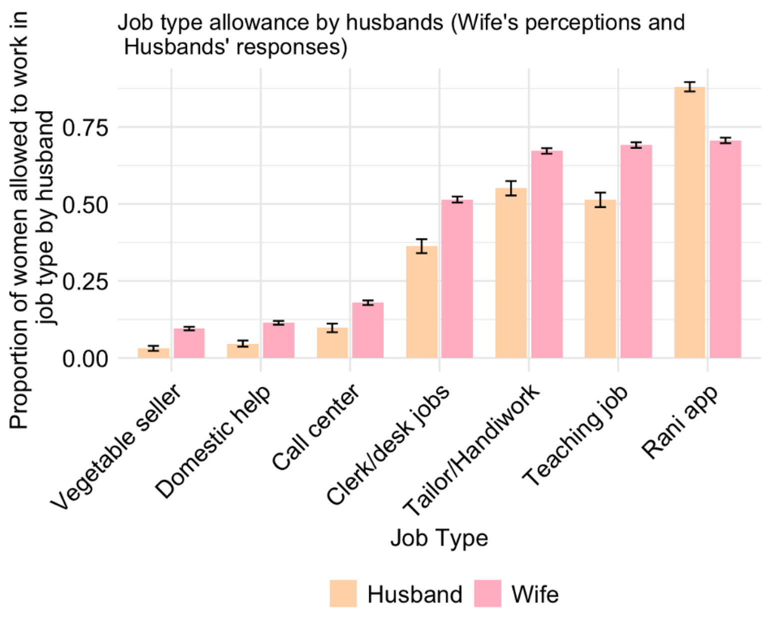

Figure A15: This graph shows the job types where husbands would "allow" their wives to work. Women stated their preferences on husbands' responses and husbands stated their own preferences. These were job preferences collected at Baseline and include a comparison with the Rani App job. Error bars represent standard errors.

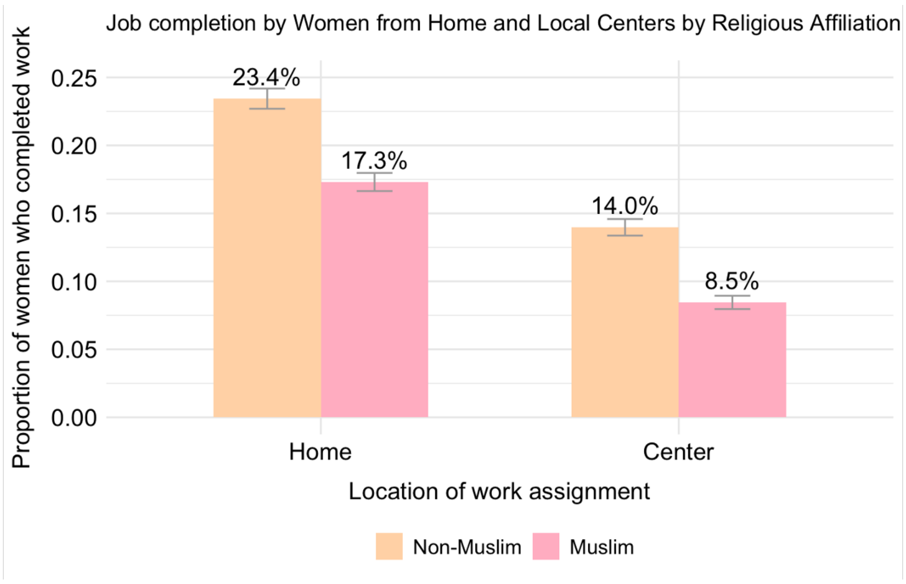

Figure A16: This graph shows the job completion rates for women from home and office separated by Non-Muslim and Muslim women. Non-Muslim women were much more likely to complete all the job tasks (15,000 tasks) from home and from offices than Muslim women. Orange bars represent Non-Muslim women and pink bars represent Muslim women. Error bars represent standard errors.

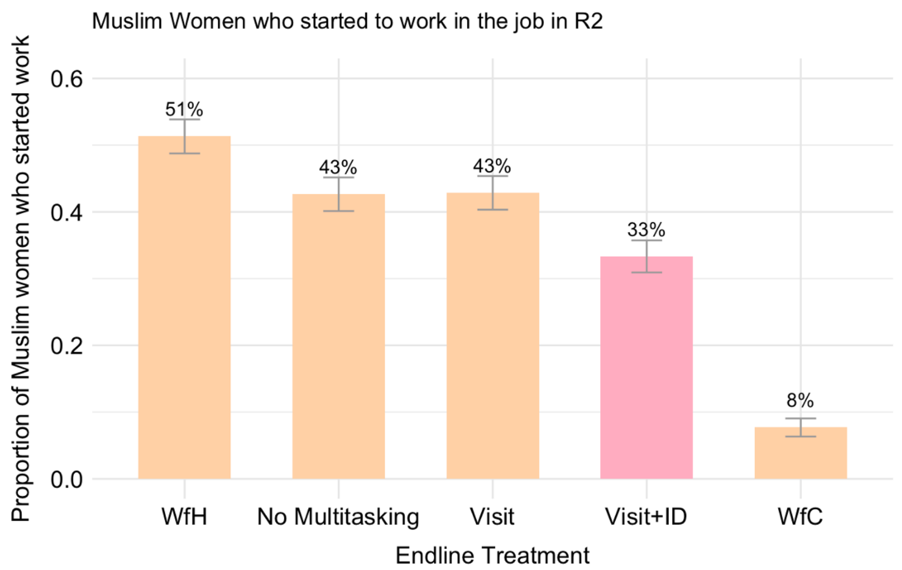

Figure A17: This graph shows the job take-up rates in Round 2 for Muslim women by the Endline experiment treatment arms. WfH and WfO are the work-from-home and work-from-office (local) treatment arms. For all the other arms, women continue to WfH but with added conditions. The No Multitasking arm allows women to work from home with no multitasking permitted by introducing task expiration and notifications that need immediate attention. The Visit only arm allows women to work from home but they need to visit a local job office every day to receive a code to unlock their application. The Visit and ID arm allows women to work from home but they need to visit the local office for the code daily and wear a work ID above their clothes while walking to and from the office. This Visit and ID treatment arm (pink bar) is the social signaling arm, which seems to be quite costly for Muslim women. There are still additional constraints that restrict them from working from offices (WfO) possibly due to the norms of domesticity, particularly patriarchal prohibition. Error bars represent standard errors.

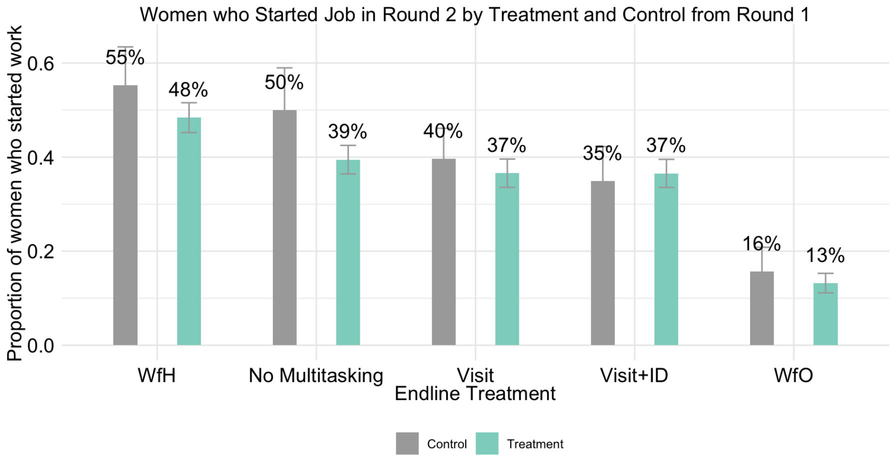

Figure A18: This graph shows the job take-up rates in Round 2 for women for the Endline experiment treatment arms by whether or not they were assigned to a Treatment arm at Baseline. "Treatment" is the set of the women assigned to one of the six treatments at Baseline, and "Control" is the set of women not assigned to any treatment at baseline. WfH and WfO are the work-from-home and work-from-office (local) treatment arms. For all the other arms, women continue to WfH but with added conditions. The No Multitasking arm allows women to work from home with no multitasking permitted by introducing task expiration and notifications that need immediate attention. The Visit only arm allows women to work from home but they need to visit a local job office every day to receive a code to unlock their application. The Visit and ID arm allows women to work from home but they need to visit the local office for the code daily and wear a work ID above their clothes while walking to and from the office. The graph shows that the take-up of Endline treatment arms was not statistically significantly different between the treatment and control groups. Error bars represent 95% confidence intervals.

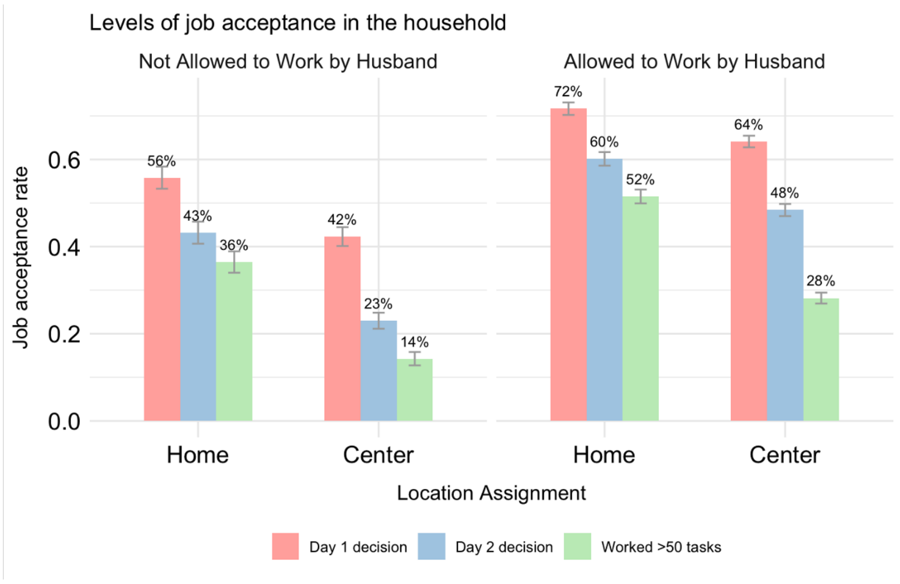

Figure A19: This graph shows the decision-making on job acceptance from home or office in the household by whether or not women were allowed to work by their husband. Allowance to work in any job by husband is self-reported by the wives in the baseline survey before provided with the job offer. Women who were not allowed by their husbands had a lower take-up in the Day 1 decision and had a sharper decrease in take-up on Day 2 (considering the families may be more restrictive). Error bars represent standard errors.

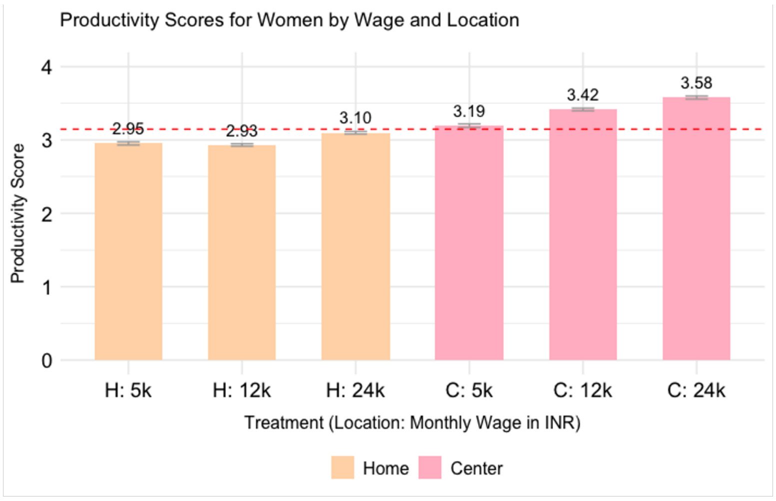

Figure A20: This graph shows the productivity scores for women for each of the treatments assigned. The treatment assignments were to a digital job either from (H) or from local offices (C) for low (5k INR), medium (12k INR), and high (24k INR) monthly wage levels. The red dashed line shows the median productivity score for the entire sample. Women from offices had higher productivity scores than women from home. The orange bar represents productivity scores from home and pink bars from local offices. Error bars represent standard errors.

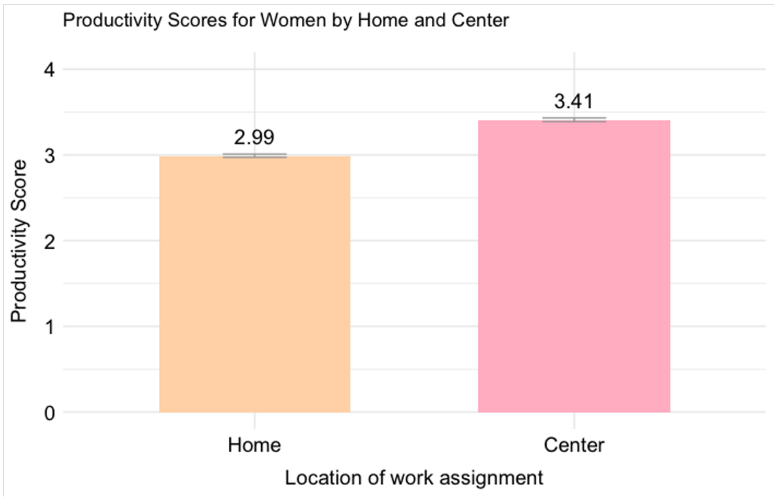

Figure A21: This graph shows the productivity scores for women for home and office (combining all wage levels). Individual average productivity is higher from the office. Error bars represent standard errors.

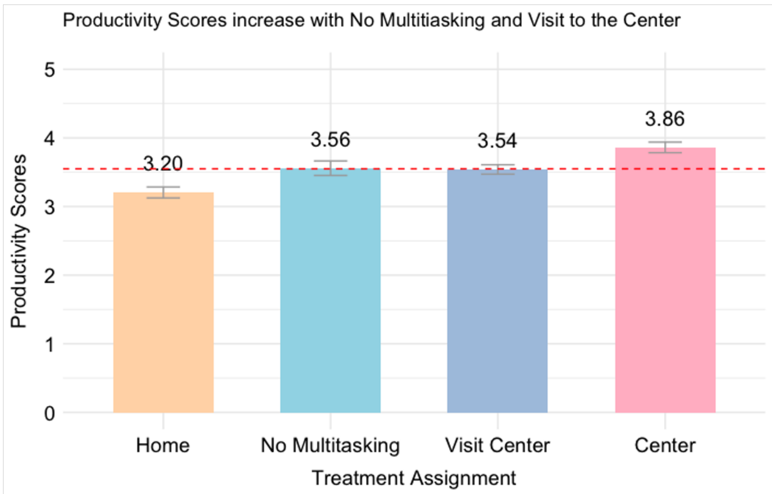

Figure A22: This graph shows the productivity scores for women for four of the Endline treatment arms: WfH, No multitasking, Visit office, and WfO. The red dashed line shows the median productivity score for the entire sample. Women in the no multitasking or visit office arms also had higher productivity than women in the WfH only arm. Error bars represent standard errors.

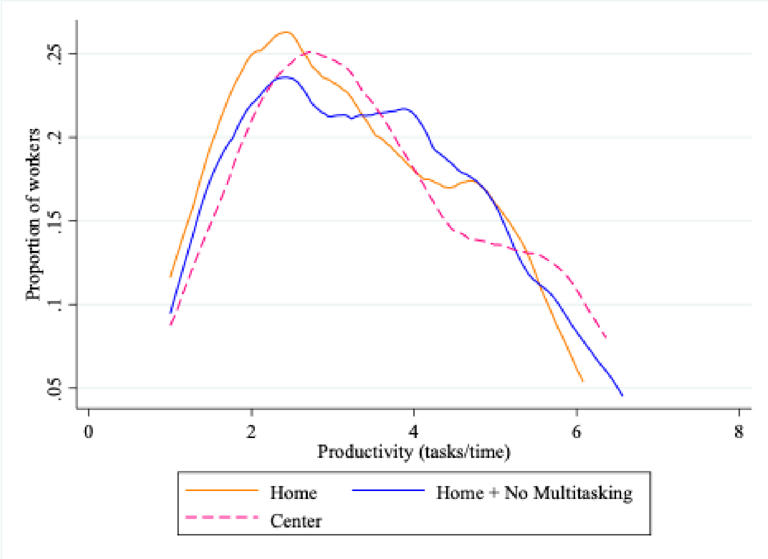

Figure A23: This graph shows the productivity scores for women for three of the Endline treatment arms: WfH, No multitasking, and WfO. Women in the no multitasking or visit office arms also had higher productivity than women in the WfH only arm.

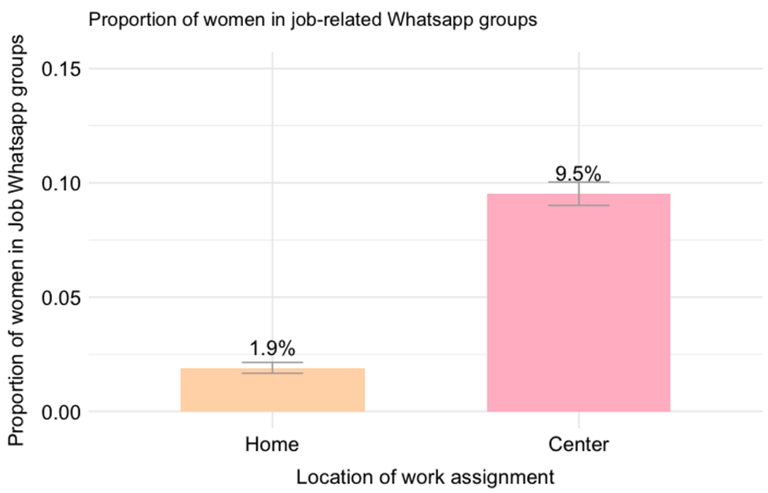

Figure A24: This graph shows the proportion of women who are in any Rani-related WhatsApp groups to discuss the job or other related matters. Women from offices are much more likely to be a part of these groups than women from home. Error bars represent standard errors.

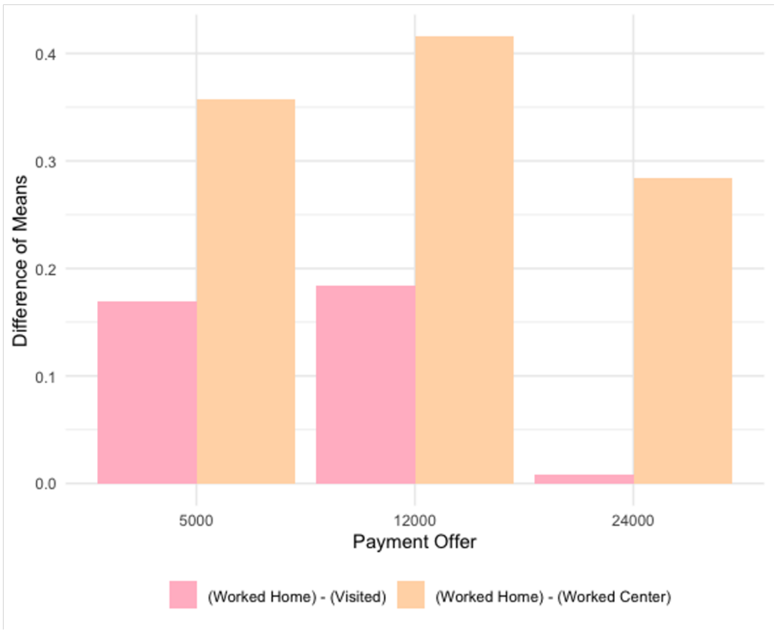

Figure A25: This graph shows the difference in means between job take-up rates at each wage level (5k, 12k, 24k INR) for starting work from home only with other treatment arms: WfH minus WfH with visiting office and WfH minus WfO. At the 24k INR wage level, the difference between WfH and WfH with office visit is almost zero. This suggests that paying women higher wages could overcome the cost associated with visiting offices but not of actually working from offices.

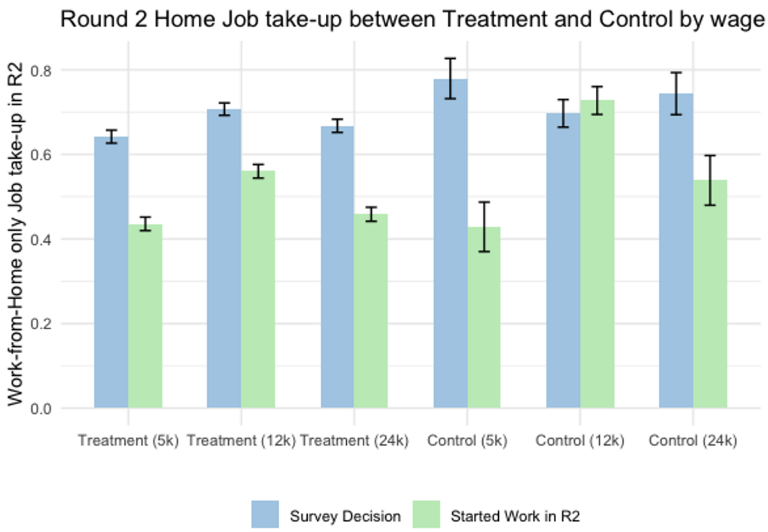

Figure A26: This figure shows the job take-up rates for Work-from-Home jobs as measured during the survey and in starting work in Round 2 after the endline survey. The graph compares the results at the three randomized wage levels for both the treatment and control groups from baseline. From this graph, we can see a non-monotonic relationship between job take-up and wage level for both the treatment and control groups in the second round of work.

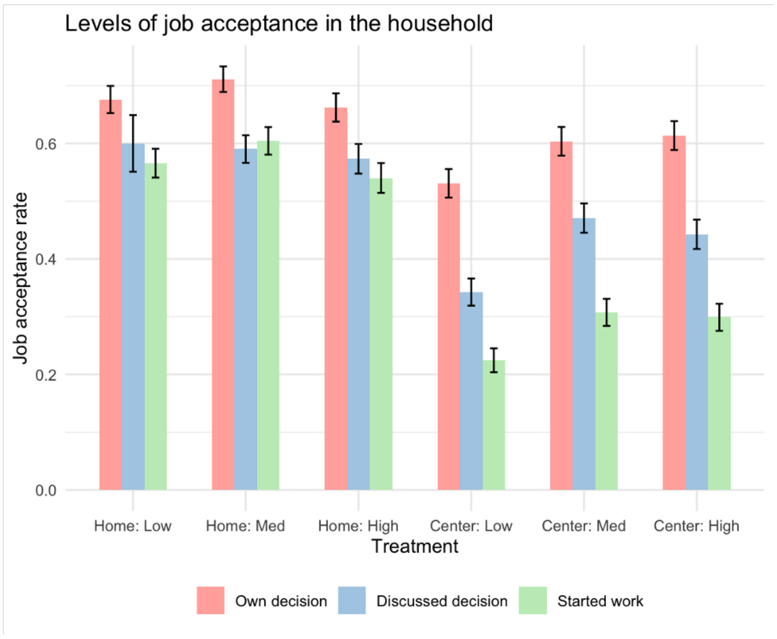

Figure A27: This figure shows the job take-up rates during the first baseline survey without the direct influence of others in their family ("Own Decision"), take-up after 1-2 days of the job offer when women may have discussed the job with others ("Discussed Decision"), and actual starting of the work ("Starting Work") for each of the six treatment arms. Difference in job take-up is higher between Own Decision and Discussed Decision for Work-from-office treatments, and between Discussed Decision and actual start of work. Error bars represent the standard errors.

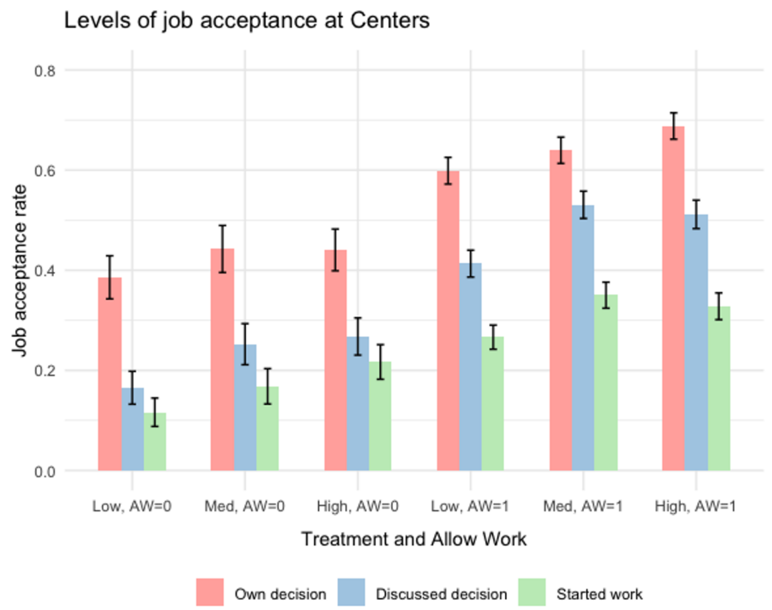

Figure A28: This figure shows the job take-up rates during the first baseline survey without the direct influence of others in their family ("Own Decision"), take-up after 1-2 days of the job offer when women may have discussed the job with others ("Discussed Decision"), and actual starting of the work ("Starting Work") for only the Work-from-office treatment arms ("Low" is for low wage, "Med" is for medium wage, and "High" is for high wage) for two types of women. The first type is one who is generally "allowed to work" by their husbands (AW=1), and another who is "not allowed to work" by their husbands (AW=0). Difference in job take-up is higher between Own Decision and Discussed Decision for women not allowed to work, and their Starting Work rates are very similar to their Discussed Decision. Error bars represent the standard errors.

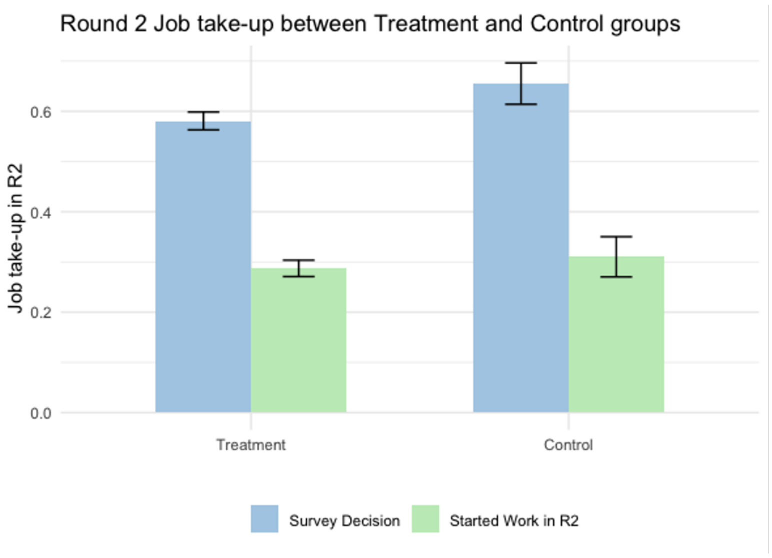

Figure A29: This figure shows the job take-up rates during the endline survey and the actual start of work for Round 2 jobs provided after the endline survey for the treatment and control groups. Error bars represent the standard errors.

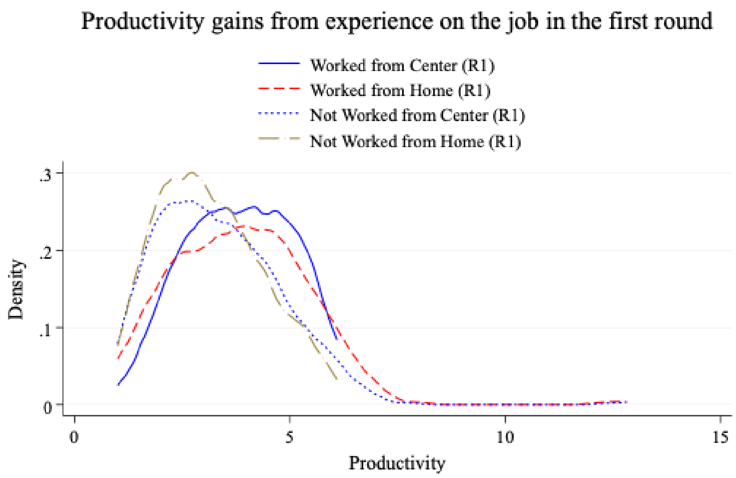

Figure A30: This density plot shows the Round 2 productivity distributions for women who worked and did not work from home and from office in Round 1 to see the productivity gains from experience on the job in the first round.

Figure A31: This figure shows the difference in means from the job take-up rate for Work-from-Home with each of the other four treatment arms at endline. These differences are calculated for two types of women who are classified by whether or not they are allowed to work by their husbands. Women who are assigned to the “No multitasking arm” from home are 19 pp less likely to work than if offered Work-from-Home as it is, for women who are not allowed to work. Each of the differences in means are labeled on top of each bar.

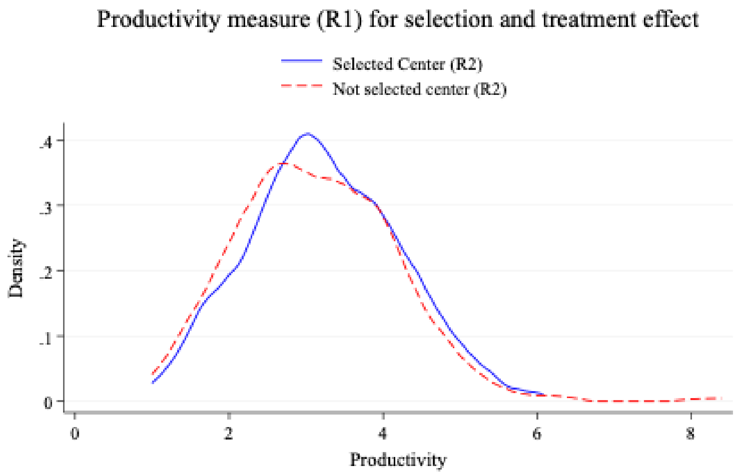

Figure A32: This density plot shows the Round 1 productivity distributions for women who selected office at endline versus those who did not. The distribution is shifted slightly right for women who had selected the office, indicating a small selection effect.

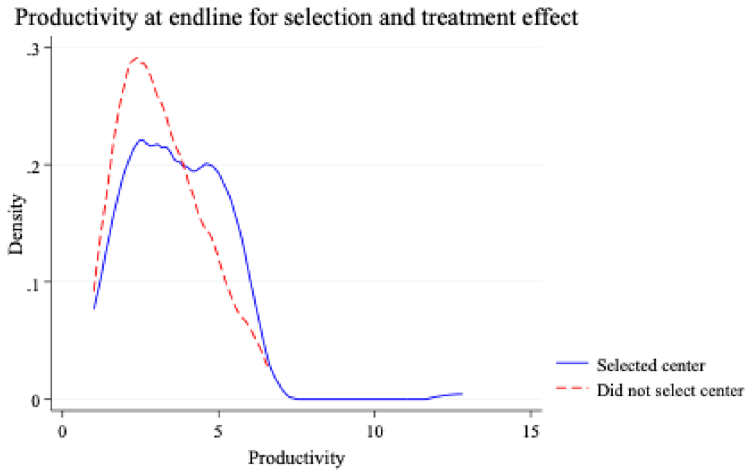

Figure A33: This density plot shows the Round 2 productivity distributions for women who selected office at endline versus those who did not. The distribution is shifted slightly right for women who had selected the office, indicating a small selection effect.

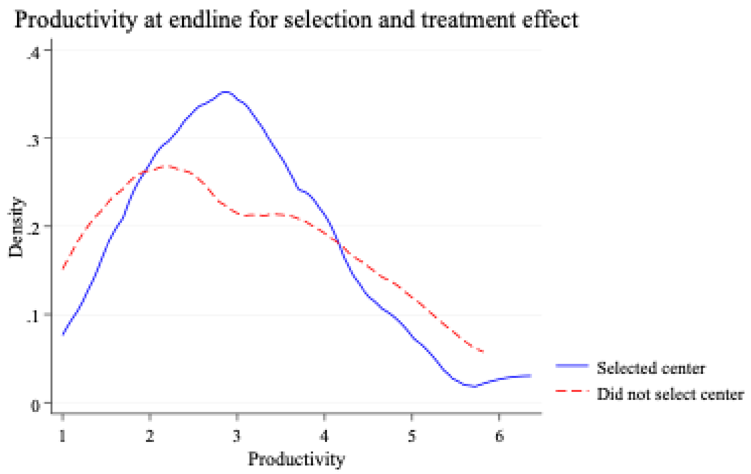

Figure A34: This density plot shows the Round 2 productivity distributions for women who selected office at endline versus those who did not for women who are allowed to work (progressive). The distribution is shifted slightly right for women who had selected the office, indicating a small selection effect is driven by those who are more allowed to work.

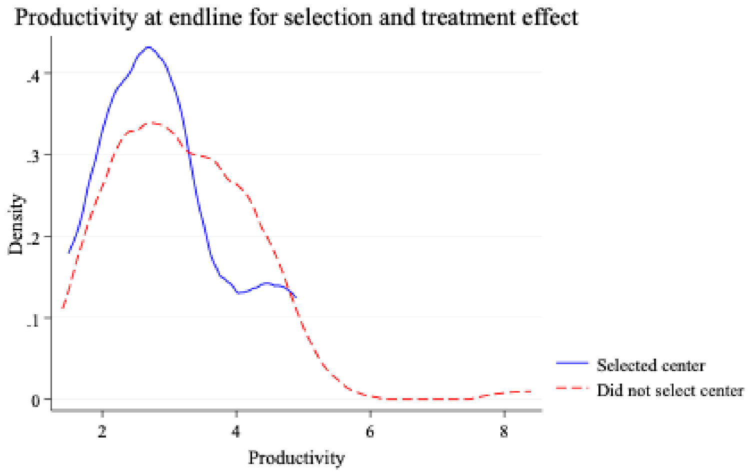

Figure A35: This density plot shows the Round 2 productivity distributions for women who selected office at endline versus those who did not for women who are not allowed to work (not progressive). The distribution is shifted slightly left for women who had selected the office, indicating that there is no selection effect for women not allowed to work into the office based treatment arms.

Tables

Table A1: Effect of mental health indicators on working

	Worked	Worked	Own D.	Own D.	Discussed D.	Discussed D.
main						
Tension Index	0.226***		0.201***		0.259***	
	(0.043)		(0.052)		(0.048)	
PHQ-8	0.018*		0.025**		0.035***	
	(0.011)		(0.010)		(0.009)	
Depressed at all		0.303***		0.285***		0.447***
		(0.085)		(0.096)		(0.063)
Constant	−1.129***	−1.114***	0.026	0.065	−0.510***	−0.474***
	(0.130)	(0.120)	(0.116)	(0.104)	(0.086)	(0.072)
Observations	2859	2859	2838	2838	2792	2792

Notes: This table shows the effect of mental health indicators on having worked in the job. Results are shown from a logistic regression controlling for each treatment and strata fixed effects. All standard errors are clustered by strata, and controls are added. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Balance table by treatment arms

		(1)		(2)		(3)		(4)		(5)		(6)		(7)		(1)-(2)	(
		1		2		3		4		5		6		7			
Variable	N	Mean/(SE)	N	Mean/(SE)	N	Mean/(SE)	N	Mean/(SE)	N	Mean/(SE)	N	Mean/(SE)	N	Mean/(SE)	N	P-value	N
Age	488	32.35	500	32.74	449	32.54	483	32.69	468	32.11	471	32.76	459	32.73	988	0.41	937
		(0.28)		(0.26)		(0.29)		(0.28)		(0.28)		(0.28)		(0.30)			
Family size	488	5.00	500	4.91	449	5.01	483	5.07	468	4.99	471	4.97	459	5.01	988	0.43	937
		(0.09)		(0.08)		(0.09)		(0.09)		(0.11)		(0.12)		(0.10)			
House ownership (=1)	360	0.56	375	0.54	330	0.59	343	0.60	328	0.57	338	0.57	335	0.56	735	0.65	690
		(0.03)		(0.03)		(0.03)		(0.03)		(0.03)		(0.03)		(0.03)			
Open caste (=1)	370	0.49	341	0.51	326	0.47	340	0.46	341	0.52	334	0.49	335	0.50	711	0.60	696
		(0.03)		(0.03)		(0.03)		(0.03)		(0.03)		(0.03)		(0.03)			
Husband monthly income (INR)	488	19567.21	500	21002.00	448	20218.75	483	19431.99	468	20347.04	471	20376.22	458	23230.79	988	0.24	936
		(761.46)		(1162.55)		(666.62)		(594.07)		(680.71)		(766.90)		(1957.28)			
Has child below 8 (=1)	488	0.57	500	0.51	449	0.59	483	0.53	468	0.58	471	0.53	459	0.53	988	0.08	937
		(0.02)		(0.02)		(0.02)		(0.02)		(0.02)		(0.02)		(0.02)			
Hindu (=1)	488	0.51	500	0.52	449	0.57	483	0.52	468	0.56	471	0.48	459	0.53	988	0.96	937
		(0.02)		(0.02)		(0.02)		(0.02)		(0.02)		(0.02)		(0.02)			
Highest education attained	488	10.96	500	10.82	449	11.14	483	11.18	468	11.11	471	10.89	459	11.07	988	0.87	937
		(0.14)		(0.14)		(0.15)		(0.14)		(0.14)		(0.14)		(0.15)			
In-laws living in HH (=1)	488	0.44	500	0.40	449	0.43	483	0.42	468	0.43	471	0.36	459	0.41	988	0.22	937
		(0.02)		(0.02)		(0.02)		(0.02)		(0.02)		(0.02)		(0.02)			
Aspirational monthly income (INR)	488	39705.02	500	41618.00	449	42158.13	483	39546.58	468	37107.91	471	68301.49	459	42511.98	988	0.37	937
		(1274.84)		(2324.66)		(3483.65)		(1020.45)		(931.51)		(21472.26)		(2590.73)			
Allowed to work (=1)	471	0.72	474	0.70	435	0.74	467	0.72	450	0.75	454	0.69	445	0.69	945	0.52	906
		(0.02)		(0.02)		(0.02)		(0.02)		(0.02)		(0.02)		(0.02)			
PHQ-8	488	4.15	500	4.73	449	4.33	483	4.31	468	4.29	471	4.56	459	4.33	988	0.05	937
		(0.20)		(0.20)		(0.21)		(0.20)		(0.21)		(0.22)		(0.21)			
Tension	358	22.13	353	22.27	346	22.42	374	22.83	361	22.06	344	22.52	355	22.27	711	0.95	704
		(0.53)		(0.53)		(0.53)		(0.50)		(0.54)		(0.52)		(0.55)			

Notes: This table shows the balance table comparing the each of the seven treatment arm means. The pairwise t-test shows that the groups are balanced on baseline characteristics such as age, family size, house ownership, caste, husband incom

B. Appendix: Data Collection and Design

Figure B1: This photo shows a snapshot of one of the Mumbai Slum Resettlement Communities where the government relocated people into from various slums around the city.

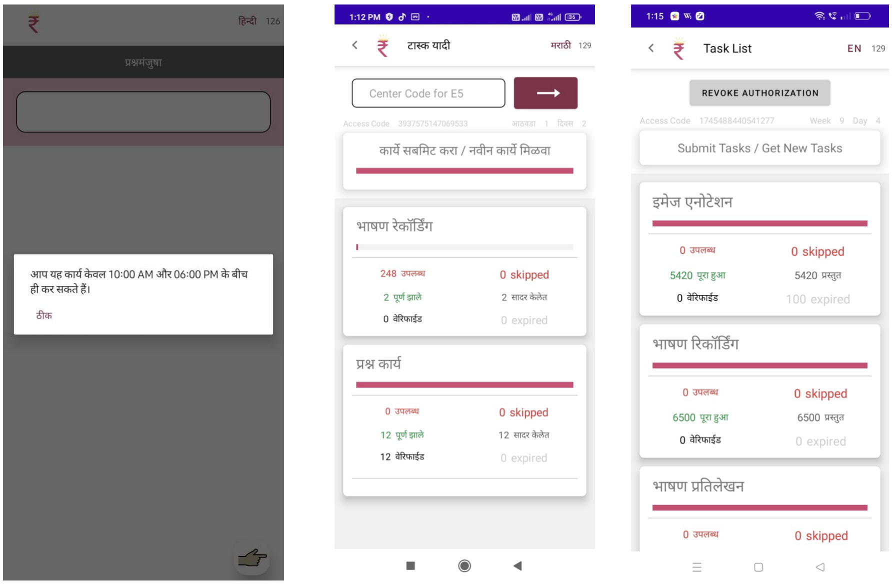

Figure B2: This photo shows a snapshot of one of the local offices where women come to work along with their children.

Figure B3: This photo shows a snapshot of one of the local offices where women come to work along with their children.

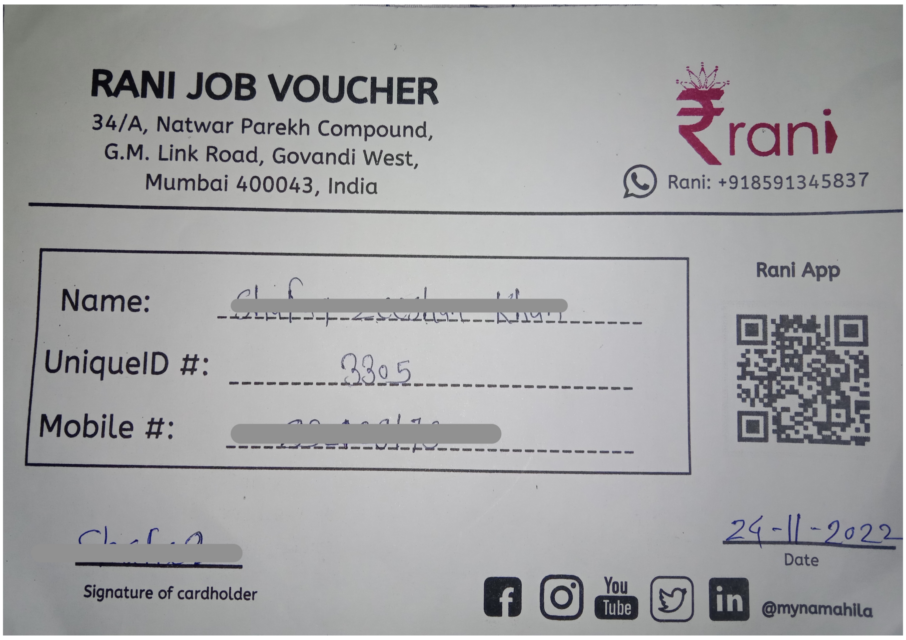

Figure B4: This is the job voucher that women received once they accepted the job offer during the baseline survey. Women could download the application directly from the voucher and call on the helpline for any queries.

C. Appendix: Spillovers

Since the experiment randomizes at the household level, women in different treatment groups and the control group could be neighbors in a highly populated setting like slum redeveloped buildings in Mumbai. Hence, we cannot prevent discussions around the job between treatment arms entirely. However, we were able to do a few things to ensure spillovers were minimal at least until women started to work on the platform. First, slum redeveloped buildings tended to be more private (where households normally kept their doors closed) and preferred to keep to themselves in many areas. Second, discussions were normally restricted to the floor level and we usually had 1-3 eligible women per floor, so the risk of spillovers was less on the same floor. Third, respondents were informed during the surveys to keep the details of the job confidential for the time-being since we did not have the bandwidth to provide jobs to everyone. Fourth, we set up three centers, each specific to a wage level per area, that were strategically located in different buildings away from each other to avoid overlapping discussions.

Fortunately, spillovers do not seem to affect decisions for job take-up at baseline or to start the first round of work. Only 7% of women had discussed the job offer with their neighbors between the Day 1 and Day 2 survey. Due to wages being an extremely private and touchy subject, women normally did not open up about their true wages to neighboring women. Hence, it is less likely for women from lower wages to have been demotivated out of starting to work at all. Women were explicitly asked about demotivation at endline, and around 5-10% of women stated to have experienced any form of demotivation, but that it did not affect their decision to take up the job. For the women who found out about the difference in wages, it was usually much later almost by the end of the project, and many did not find that problematic by trusting that the system was fair by educational qualifications, or previous work experience, or some other explanation they weren't aware of.

Spillovers between the treatment and control arms in the form of trying out the job were minimal. When women in the control group were asked at Endline if they had visited a Rani center or tried to use the Rani application, only around 5% of women in the control group had tried it. Hence, about 95% of women in the control group had not explicitly used the jobs platform or visited any job center for this work.

Spillovers between treatment groups at the time of starting work were also minimal. Only about 7% of women assigned to work from home stated at endline that they had visited a Rani center at some point. Among those who visited the center but were assigned to work from home, 30% of T1 and about 32% of T3 visited, while around 39.5% of T2 women visited.