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Gender-Specific Transportation Costs and Female Time Use: Evidence from India’s Pink Slip Program
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ABSTRACT

Reducing gender-specific commuting barriers in developing countries can have heterogeneous effects on women’s labor outcomes. We study a program that offers free bus rides for women in several Indian states (the Pink Slip program) using a synthetic difference-in-differences approach to examine impacts on transportation expenditures, time use, and labor supply. We find that the program substantially reduces bus-related expenditures. However, when considering all women together, we find no significant changes in travel time, household production, or labor supply. Beneath these aggregate effects, responses vary sharply by employment, marital status, and education. Unmarried women employed prior to the policy increase labor supply, while married women with low and medium levels of education reallocate time away from paid work toward household chores. Overall employment rates remain unchanged in the short run, highlighting that reducing commuting costs does not uniformly improve women’s labor market outcomes.

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1 Introduction

The gender disparity in commuting barriers is pervasive, affecting women in both developing and developed nations. The International Labour Organization (2017) reports that the lack of transportation decreases women's probability of participating in the labor market by 16.5 percentage points among developing countries. Can reducing commuting barriers influence women's labor supply decisions? Whether or not policies directly addressing commuting costs would help increase the female labor supply is far from obvious. On the one hand, lowering costs can increase labor supply. On the other hand, social norms regarding household chores and traveling alone could significantly impede female labor supply, as evidenced by prior studies (Fanning Madden, 1981; Turner and Niemeier, 1997; Lee and McDonald, 2003; Abe, 2011; McQuaid and Chen, 2012).

Our study sheds light on the trade-offs faced by women when commuting costs are reduced. We do so by utilizing the implementation of the *Pink Slip* program that provides free bus passes to women in several states of India. India is a pertinent setting for exploring this issue. There is an overwhelming gender gap in commuting time and modes used. The 2011 Census of India reports that 30.2% of women travel to work on foot, and only 24.6% use any transit or personal vehicles, highlighting the limited access to transportation options for many women. In contrast, only 20% of men travel on foot, and more than 50% of men use some transportation. There is also evidence that women use slower modes of transportation to commute to work, as faster modes are usually more expensive (Anand and Tiwari, 2006). Concurrently, female labor force participation is low in India, at a rate of 28.3% of the working-age population as of 2019, significantly lower than the average of 46% in low- and middle-income countries.[1]

We leverage the *Pink Slip* programs' state-wide roll-out in Punjab and Tamil Nadu in April and May 2021, respectively. While Delhi also introduced this program in November 2019, data limitations preclude us from including it in our sample.[2] To identify the causal impact of the program on women's labor outcomes, we collated data from several sources. Our main empirical analysis is based on the Consumer Pyramids Household Survey (CPHS) data maintained by the Centre for Monitoring the Indian Economy (CMIE). The rich CPHS data is a panel of about 160,000 households across all major Indian states after 2014. It includes comprehensive information not only on household expenditures, members' demographic characteristics, and employment status but also on their

[1]Data are from World Bank's Gender Data portal. According to the most recent female labor force survey by India's Ministry of Statistics and Program Implementation, it increased to 37%.

[2]The CMIE, our main data source in this paper, started collecting information on individual time usage after Delhi started implementing the *Pink Slip* program. We therefore cannot include Delhi in our sample.

time use patterns and allocation of time on various activities. We complement this analysis with a large primary survey of women conducted in Delhi after the program's launch there, as well as a separate 2023 survey conducted by the Citizen Consumer and Civic Action Group (CAG) in Tamil Nadu. Both surveys provide additional descriptive evidence supporting our main findings.

Our identification approach compares women in treated states (i.e., Punjab and Tamil Nadu) to women in other states, which serve as our control group. The implementation of the policy in 2021 provides temporal variation. To address endogeneity concerns, we implement a synthetic differences-in-differences strategy (SDID) proposed by Arkhangelsky, Athey, Hirshberg, Imbens and Wager (2021). This approach combines the synthetic control method (Abadie and Gardeazabal, 2003) with the difference-in-differences strategy. We compare the pre-trends in our treated and the synthetic control groups using event study models and do not discern differential trends.

We first examine the effect of the treatment on commuting expenditure. In doing so, we determine if women's travel demand is responsive to the cost of transportation. We find evidence that employed women's demand for transportation is price sensitive: following the free bus scheme, they reduce travel time—consistent with a shift toward faster modes such as buses—while simultaneously experiencing declines in bus-related expenditures due to using the scheme. Overall expenditure on travel, specifically on a category that includes buses, declined by ₹48 (Indian rupee) per month for households with women in treated states compared to those in control states. Findings from the Delhi and CAG surveys corroborate these results at the individual level. In particular, the Delhi Primary Survey shows that new female bus users report negligible transportation costs after the policy was introduced, in contrast to substantial expenditures on other modes of transport prior to switching to buses.

We then investigate whether women in treated areas change the time spent traveling and, if so, how any time savings are reallocated across other activities such as household chores and labor supply. When considering all women together—including those who are employed, unemployed, and out of the labor force—we find no statistically significant changes in travel time or time devoted to household chores. Short-term employment outcomes also do not show any shifts. These aggregate null effects mask offsetting responses across groups of women that vary by employment status, marital status, and education. Women employed at baseline reduce their daily travel time by 10.2 minutes, increase time spent on domestic chores by 11 minutes and time spent working by 6.8 minutes per day. In contrast, women who were unemployed prior to the policy reduce time spent on household chores by 1.6 hours per day. Among women employed at baseline, marital status plays a central role in shaping time reallocation. Unmarried employed women at baseline increase their work hours by economizing on both travel time and household activities. However, these gains only accrue to better-educated unmarried women. Married employed women, by contrast, reallocate time toward household production and reduce their labor supply.

To unpack this further, we examine time reallocation among married women employed at baseline by education level. We find that the decline in labor supply among married employed women is concentrated among those with low and medium levels of education (i.e., below higher secondary schooling).

We then present a simple model of household labor supply and home production to illustrate a mechanism consistent with these patterns. The model shows how indivisible household chores that require both a fixed time input and a complementary travel component can generate intra-household reallocation when women's commuting costs fall, with the direction of re-optimization shaped by the gender wage gap.

Consistent with this interpretation, we find that married men adjust their time use in the opposite direction: husbands of medium-education women increase their labor supply, while husbands of both low- and medium-education women reduce their share of time spent on domestic work by the couple. Our findings indicate that while the free bus initiative enables highly educated and unmarried women to increase market work, married women with lower levels of education respond by reallocating time away from paid work and toward household production. These patterns are consistent with household-level constraints emphasized in the gender norms literature (e.g., Jayachandran, 2021; Dinkelman and Ngai, 2022), though we do not directly identify norms.

Our results have important policy implications. Without a careful accounting of heterogeneous responses across different groups of women, average effects can obscure meaningful trade-offs and lead to incomplete policy conclusions. We show that gender-specific transportation subsidies, while potentially redistributive, do not uniformly improve women's labor market outcomes. In the short run, gains accrue primarily to highly educated women who were employed before the policy, a group that constitutes a relatively small share of the female workforce in India.

Our paper complements a growing body of work studying the effects of barriers to women's mobility and access to public transport systems on female labor force participation (Field and Vyborny, 2022; Martinez et al., 2020; Alam et al., 2021; Lei et al., 2019; ILO, 2017; Petrongolo and Ronchi, 2020). Farré et al. (2022) show that a 10-minute increase in commuting decreases the likelihood of married women participating in the labor market by 4.6 percentage points in the U.S.. Using a job search model where commute matters, Le Barbanchon et al. (2021) estimate that approximately 10% of the wage gap between men and women upon re-employment in France could be attributed to differences in the willingness to commute across genders. Black et al. (2014) show that metropolitan areas' commuting times explain the considerable variation across US cities in married women's labor force participation. In a closely related paper, Field and Vyborny (2022) demonstrate that women-only buses increase female job search in Pakistan.[3] We extend this literature by highlighting that demand for transportation is responsive to price changes for women, but there is heterogeneity by education and marital status. Our paper highlights that in the presence of restrictive gender norms, reducing commuting costs alone may not be enough for all women to increase work hours or participation in the labor market.

The second strand of literature we connect to analyzes the effects of reductions in commute times, often by providing transit subsidies in randomized control experiments, on job search and employment creation (Franklin, 2018; Abebe et al., 2016; Phillips, 2014; Moreno-Monroy and Posada, 2018). The dominant finding in this literature is that reductions in commuting costs increase job search intensity and employment. However, recent evidence from a U.S.-based experiment finds that free public transportation for low-income individuals does not significantly affect employment outcomes, though it may improve financial and physical health (Brough et al., 2025). We demonstrate that social norms in developing countries can undermine the effects of policies that reduce commuting costs, especially for women.

The rest of the paper is organized as follows. Section 2 describes the study setting and Section 3 details the datasets. Section 4 outlines the empirical methodology. Section 5 presents results on transportation and household expenditure. Section 6 discusses time-use effects for employed women by marital status, offers a simple model of household time allocation, and explores effects for unemployed women. Section 7 examines whether food expenditure savings justify women's time reallocation toward household chores. Section 8 examines changes in employment status and labor force participation. Section 9 provides a back-of-the-envelope cost-benefit analysis. Section 10 presents robustness checks, and Section 11 concludes.

[3]Two studies also examine the Indian *Pink Slip* program. Dasgupta and Datta (2023) use a cross-sectional time-use survey to compare labor supply for women relative to men in one treated state. Our study differs in several significant dimensions. First, we do not use men as the counterfactual group since our intra-household model and empirical results indicate that the *Pink Slip* program also influences men's time use through joint household decision-making. Second, using a tighter identification and panel data, we uncover substantial heterogeneity in outcomes and across subgroups of women. The other study is ongoing work by Borker et al. (2020) who leverage a randomized control trial to assess Delhi's policy to introduce free passes and provide safety in public buses.

2 Background

2.1 Limited Utilization of Public Transport by Women

Mobility plays a crucial role in enabling access to economic opportunities, education, and social engagement. Yet, across the world, women face distinct mobility constraints. Lower earnings, greater economic dependence, and limited control over financial resources reduce their ability to afford transportation (Borker, 2022). Their travel patterns are often characterized by multi-stop trips driven by caregiving and household responsibilities rather than formal employment, making their journeys more complex and costly (Dominguez Gonzalez et al., 2020).

In India, inadequate transport infrastructure and services constrain mobility for both men and women. The substantial gender wage gap (Duraisamy and Duraisamy, 2016; Deshpande et al., 2018) and restricted access to financial systems (Khera, 2018) leave women with fewer resources to pay for transportation. As a result, Indian women are more dependent on public transport than men are, especially when they are from lower-income groups (Shah et al., 2017). However, they face additional socio-cultural and economic barriers that limit their access to public transport (Srinivasan and Rogers, 2005; Tripathi et al., 2017; Alam et al., 2021).

Safety concerns also contribute to the low rate of female ridership. Fear of harassment and a perceived lack of security on public transport deter women from using buses, especially when there are few other female passengers (Sajjad et al., 2017; Kapoor and Gade, 2024). In a survey of 3,800 students at Delhi University, Borker (2021) found that women were willing to travel 27 additional minutes per day—about 40% more time, if it meant taking a route perceived as safer. These challenges undermine women's access to mobility, with downstream effects on their participation in the labor force and public life more broadly (Astrop et al., 1996; ILO, 2017).

2.2 Pink Slip Policy—Transport Subsidy for Women

In response to these constraints, the Delhi government launched a program in November 2019 that provides free bus rides to all women in the city. Under this initiative, women receive a pink ticket (hence the name of the program) for each ride on Delhi Transport Corporation (DTC) and privately operated cluster buses. The program prompted an immediate response: within just 20 days of implementation, the share of women among daily DTC and cluster bus riders rose from 33% to 44%.[4] By March 2021, after the pro-

[4] https://shorturl.at/cAFMT, Indian Express on 10/22/2019, last accessed on 7/22/2025.

gram's launch, women made up the majority of riders on Delhi Transport Corporation buses.[5]

Following its initial success in Delhi, similar programs were adopted by Punjab and Tamil Nadu. Punjab launched its program on April 1, 2021, and Tamil Nadu followed on May 7, 2021. These programs offer free rides to women on government-operated buses. Between July 2021 and March 2022, the share of female bus commuters in Tamil Nadu increased from 40% to 61%.[6]

While the official rationale for these programs is to reduce financial barriers to mobility for women (Chakravarthy and Seth, 2024), the timing of Delhi's *Pink Slip* program—introduced just months before the 2020 Assembly elections—cannot rule out the possibility of political motivations, including an appeal to female voters. Despite some anecdotal accounts of non-compliance by drivers in Tamil Nadu, no official data is available to verify these accounts. Such non-compliance would attenuate our estimates, giving us at least a lower bound.

Appendix Table F1 lists all states that introduced free or subsidized bus fares for women between 2019 and 2024. In our analysis, we study only Punjab and Tamil Nadu due to data constraints explained in footnote 2 and to be elucidated further below.

3 Data

3.1 Consumer Pyramids Household Survey

Our main data source is the Consumer Pyramids Household Survey (CPHS). It is a longitudinal survey of households conducted by the Centre for Monitoring the Indian Economy (CMIE). Starting with the first wave in January-April 2014, the CMIE conducts three waves of surveys annually: January-April, May-August, and September-December. Each wave covers about 160,000 households from all major Indian states, maintaining a consistently high household response rate of over 80%. A multi-stage stratified survey design is deployed. The broadest level of stratification is a homogeneous region (HR), defined as a set of neighboring districts within a state that is comparable in terms of argo-climatic conditions, urbanization, female literacy rates, and number of households. Based on the 2011 India Census, the CMIE categorizes districts into 110 HRs, which remain constant over time. As described above, households in Punjab and Tamil Nadu form our treatment sample. The control group consists of the other 20 states and union territories, except those in

[5] `https://shorturl.at/vaRRO`, Hindustan Times on 8/1/2021, last accessed on 7/22/2025.

[6] `https://shorturl.at/xMzQi`, Times of India on 3/19/2022, last accessed on 7/22/2025.

the isolated North Eastern Region.[7] We display the map of HRs in Appendix Figure E1. In total, we have 96 HRs, with 8 in two treatment states and 88 in the 20 control states.

The CPHS has four sections: Consumption Pyramids (CP), People of India (PoI), Aspiration India (AsI), and Income Pyramids (InP). This study uses the CP, InP, and PoI sections. The CP is a household-level monthly survey reporting household expenditures on various kinds of goods and services, without a breakdown of individual members of multi-person households. Specifically, it asks households about their monthly expenditure on all types of transport, including expenses on a combined category of "buses, trains, and ferries" (BTF). Our study period for the CP is from November 2020 to September 2021. The InP is a monthly survey that tracks the income of each household member. We use the same study period as in the CP data.

The PoI is an individual-level survey conducted every four months. There are three waves a year: January-April, May-August, and September-December. [8] The PoI data has information on one's employment status, time usage, and demographic characteristics like gender, education level, and marital status. The PoI data records the amount of time a person spends on household work, paid and unpaid (as a trainee or volunteer) work, traveling, leisure, and personal activities. These categories add up to 24 hours for 99.9% of the observations in the data, and we drop the remaining 73 observations. The reported time on travel is spent by a person traveling from one place to another for various purposes, including work-related activities. The PoI section does not ask specific questions about time spent commuting to work or searching for a job.

We use seven waves of PoI from May-August 2020 to May-August 2022 (or from the 20th to the 26th wave). We also match the households in the PoI data to those in the CP data. Appendix Table F2 lists the study periods for the two sectional data sets.[9] We restrict our sample to women (or households having women) aged between 15 and 55 at their first appearance in the data. Appendix Table F3 lists the variables used in the

[7] The CMIE started to collect household members' time usage information in the wave of September-December 2019, while the government of Delhi started the *Pink Slip* program in November 2019. We do not include Delhi in the analysis since we do not have pre-period information on time usage. Of the eight northeastern states, there is no data for Arunachal Pradesh, Manipur, Mizoram, and Nagaland during the study period in the People of India section. For consistency, we also exclude the remaining four states (Assam, Meghalaya, Sikkim, and Tripura) located in that region. Our control sample includes two union territories, Chandigarh and Jammu & Kashmir, for which data is available.

[8] Individuals are not observed in every survey wave because they are not interviewed in every round. Hence, the panel is not balanced. Over our study period, individuals are observed, on average, in 4.7 out of 7 waves.

[9] For the PoI data analysis, we classify the January–April 2021 wave as part of the pre-period for Punjab, as three of its four months precede the policy implementation. Including this wave helps avoid misattribute any changes that occurred during this period, particularly those between January and March 2021, to the effects of the *Pink Slip* program.

analysis and their definitions. Appendix Table F4 presents the summary statistics of our study sample. Panel A displays the household characteristics as of December 2020. Differences between households in treated versus control states, in terms of rural residence, number of people, and per-capita income and expenditures, are relatively small. In panel B, we compare women in treated states to those in control states in May-August 2020. The distributions of age, marital status, and education are broadly comparable for the two groups of women. Women in treated areas are less likely to participate in the labor market, but conditional on participation, they are more likely to be employed. They also tend to spend more time on household activities and work, but less time on travel than women in control areas. A limitation of the CHPS data is that it does not inquire about the length and number of bus trips or their costs.

3.2 Auxiliary Data

In addition to the CPHS data, we draw on two primary surveys, one from Delhi and another from Tamil Nadu. The benefit of these datasets is that they have questions about bus usage, ridership, and the cost of riding buses. The drawback is that these are targeted at a selective population. We also add publicly available COVID-related data, such as daily case counts and state mobility restrictions, to support our empirical analysis.

3.2.1 Delhi Primary Survey

As explained above in footnote 7, we cannot include Delhi in our baseline analysis. To complement our inquiry, however, we use primary data collected in February 2020 by the Gesellschaft für Internationale Zusammenarbeit (GIZ), India (Mahendru, 2022). This survey is specifically designed to evaluate changes in bus usage among women in Delhi following the implementation of the *Pink Slip* program. The survey collected responses from 2,025 women, of which 1,294 had been using the bus before the program's introduction; we refer to this group as "continuous users." Additionally, 231 respondents who began using buses after the program's introduction are termed "new users." The remaining 500 respondents who did not use buses before or after the program are labeled as "non-users."

The sample was randomly selected at major attractions and generation points across Delhi, as shown in Appendix Figure E2.[10] Appendix Table F5 provides some summary statistics of the survey sample. Compared to non-users, bus users (both new and continu-

[10]The generation points are all major locations within the city that tend to be trip origins or destinations. These include major work areas, shopping districts, and schools.

ous) are predominantly aged between 31 and 40, more often homemakers, more likely to reside in households with monthly incomes exceeding ₹20,000, and less inclined to travel for work. Given these differences, we constructed a comparable sample of non-users, new users, and continuous users using propensity score matching. This matching is based on the following variables: age, occupation,[11] total average monthly household income and expenditure on travel, ownership of private vehicles, and driving knowledge.

Our study sample of the Delhi primary survey is the matched sample ($n = 1,290$) consisting of 184 non-users, 182 new users, and 924 continuous users. Compared to the treated sample in the CPHS data, the matched Delhi sample is characterized by higher levels of education and annual household income, as it is predominantly urban. Approximately 68% of the bus users in the matched sample hold a graduate degree, and 85% of them report an annual household income of over ₹240,000.[12]

Perceptions of Buses In Table 1, we compare perceptions of buses between non-users and users (panel A), as well as between new users and continuous users (panel B) in the post-program period. We examine the differences in their perceptions of five aspects: 1) affordability and availability of free bus transit; 2) safety regarding accidents, crashes, threats, and thefts; 3) connectivity; 4) bus frequency, waiting time, travel duration, and unnecessary stops; and 5) accessibility to bus stops. Panel A shows that non-users consistently find bus travel less satisfactory across all five dimensions compared to users. They are particularly concerned about safety issues. The average safety rating among non-users is 1.63 (on a 1-5 scale where 1 = highly unsatisfactory and 5 = highly satisfactory), indicating low satisfaction with safety. Panel B shows that new users tend to give a lower rating to safety (0.13 points lower) compared to continuous users, but higher ratings to affordability and the availability of free commutes. Specifically, new users, on average, rate the affordability and availability of free bus commutes 0.19 points higher than continuous users, and this difference is statistically significant at a 1% level. These results suggest that when it comes to transportation, women prioritize not only safety concerns but also *affordability*. Reducing costs in public transportation thus has the potential to encourage women to choose buses as a viable option for job search and commuting.

[11]The occupation variable consists of the following categories: service, business, informal worker, daily wager, homemaker, and student.

[12]In contrast, in the CPHS data, about 56% of households in treated states reported an annual household income exceeding ₹200,000 as of December 2020 (panel A of Appendix Table F4).

3.2.2 CAG Survey

The Citizen Consumer and Civic Action Group (CAG) conducted a large-scale survey in 2023 to evaluate the impact of Tamil Nadu's fare-free public bus program for women (Narayanan, 2024). The survey involved face-to-face interviews with 3,000 female bus users, 500 each from six cities: Chennai, Coimbatore, Salem, Tiruvarur, Tirunelveli, and Tiruvannamalai. For the purpose of our analysis, we restrict the sample to women aged 18 to 50, resulting in 2,330 respondents.[13] We report some summary statistics in Appendix Table F6, the age distribution of which is similar to that observed in the Delhi Primary Survey. The table also shows that approximately 63% of the sample are employed, and about 31% report having no income. In Figure 1, we present the top four reported reasons for using free buses. The majority (85%) cite *saving money* as their primary reason, followed by convenience (28%), the absence of alternative transport options (17%), and saving time (14%), indicating that *affordability* is a major concern.

3.2.3 COVID-19 Data

Since our study period overlaps with the pandemic period, we obtain COVID-19 case data from Wahltinez et al. (2022). We also use the 2011 Indian Population Census to obtain district-level characteristics like population. We combine the two data sets and construct average daily new confirmed cases as a share of state population. We include this variable in our regressions to account for the potential effects of COVID-19 on outcomes like labor market participation. In Appendix Figure E3, we show the trends in states' monthly average of daily new confirmed cases per 1,000 population. The overall patterns are broadly similar across states, with the median trend for the 20 control states closely tracking those of Punjab and Tamil Nadu. To address further concerns that different states experienced different levels of mobility restrictions, we also use data from Hale et al. (2021) on the share of days each month that state governments imposed a shutdown on public transportation.

4 Empirical Strategy

States that implemented the *Pink Slip* program may differ from other states. To address this concern, we employ the synthetic difference-in-differences strategy (SDID) proposed by Arkhangelsky et al. (2021). The SDID re-weights the control units to make their time

[13] We use the 18–50 age range instead of the 15–55 range used in the CPHS data because the CAG survey categorizes respondents into the following age groups: 18–20, 21–30, 31–40, 41–50, 51–60, and 61 and above.

trend parallel to the treated units and then applies a DID analysis to the re-weighted panel. This method constructs a synthetic counterfactual for causal estimation. Although in our setting the treatment is implemented at the state level, the CPHS survey's broadest level of stratification is the HR level. Therefore, we construct an HR-level panel using the CPHS data. This allows us to derive unit and time weights for each control HR using the SDID method. We then apply these weights to reweigh our individual- and household-level data for analysis. A detailed explanation is provided in Appendix A.1.

To estimate the impact of the *Pink Slip* program on women (or households with women), we employ two regression specifications for individual (or household) i in region j and time t weighted by the individual (or household) sampling weight, along with the HR unit and time weights derived from the SDID. Starting with a standard stacked event-study design

$$Y_{ijt} = \alpha_i + \alpha_t + \sum_{t=a}^{b} \beta_t \cdot Treat_j \times \mathbb{1}(Time = t) + \varepsilon_{ijt}, \tag{1}$$

where Y_{ijt} are outcome variables such as household monthly expenditure on transport and individual time usage on travel. The dummy variable $Treat_j$ takes the value one if the individual or household resides in a state that implemented the *Pink Slip* program and zero otherwise. $\mathbb{1}(Time = t)$ takes the value one in period t after the event and zero otherwise. Since the time units differ between the CP and PoI data, we set t as one month for the household consumption regression and four months (equivalent to one wave) for the individual-level time use regression. For example, in the household-level data (CP data), $Time = 0$ corresponds to one month before the event; in the individual-level data (PoI data), $Time = 0$ corresponds to one wave (equivalent to four months) before the event. The omitted base period (or $Time = 0$) is the wave (or month) of the survey before the start of the program.

In a separate specification, we pool the pre- and post-treatment periods to estimate

$$Y_{ijt} = \alpha_i + \alpha_t + \beta \cdot Treat_j \times Post_t + \varepsilon_{ijt}. \tag{2}$$

In both equations (1) and (2), α_i are individual (or household) fixed effects that control for all time-invariant characteristics of an individual (or a household). α_t represents the time-fixed effects, which account for common temporal shocks. In the household consumption analysis, α_t corresponds to month fixed effects (measured in absolute terms of calendar month rather than relative to the policy start). Meanwhile, in the analysis of PoI data, α_t represents wave fixed effects (also in absolute terms). Appendix Table F2 provides a detailed definition for $Time_t$ and $Post_t$. To account for the impact of the pandemic on people's behavior, we also control for average daily confirmed COVID-19 cases as a share of the population. Because the treatment is at the state level, we cluster standard errors at the state level for statistical inference. Our parameters of interest are β_t and β.

5 Treatment Effect on Transportation Expenditures

We begin our analysis by estimating the treatment effect on household transportation expenditures using the CPHS data, complemented by supporting evidence from the Delhi and CAG surveys. *A priori*, we expect different outcomes depending on substitution patterns. To the extent that women who previously used paid public buses continue to do so after the program makes these rides free, or switch to free bus transit from costlier modes (such as taxis, rickshaws, or privately operated bus lines), we would expect household expenditures on transportation and buses to decrease. Conversely, we would expect no change if women switch from walking to buses. In the absence of spillovers to male members within a multi-person household, the average effect will depend on the relative prevalence of these substitution patterns.

5.1 Evidence from the CPHS Data

To examine the impact of the *Pink Slip* program on monthly *household* transportation expenses, we estimate equation (2) using four outcome variables: expenditure on bus, train, and ferry transportation (BTF); expenditure on all kinds of transportation; the share of BTF in total transport expenditure; and the share of BTF in total household expenditure. We report the results in Table 2. In column 1, we find that households in treated states spend ₹26 less on BTF compared to those in control states after the program's implementation. While bus fares vary across states, in 2024, the fare in Punjab was around ₹1.5 per kilometer, whereas in Tamil Nadu, it was ₹4 for up to 4 kilometers and ₹10 for 18 to 20 kilometers.[14] A reduction of ₹26 in expenditure on BTF could translate to approximately 17 kilometers of free travel in Punjab and at least 20 kilometers in Tamil Nadu. Additionally, households in treated states spend ₹48 less on overall transportation compared to their counterparts in control states in the post-periods (column 2).[15]

[14]See https://shorturl.at/lgsp7 and https://shorturl.at/5SOPQ, last accessed on July 22, 2025.

[15]This larger decline in total transportation spending, relative to the reduction in BTF expenditure, suggests that women in the household may either be substituting away from other paid modes of transport toward free buses, or taking over trips that were previously made by male household members using paid transport. Due to data limitations, we are unable to distinguish between these possibilities.

Columns 3 and 4 highlight how the *Pink Slip* program affected the composition of household transportation spending. Column 3 shows that the share of BTF in total transport expenditure decreased by 6.0 percentage points for treated households in the post-periods. In Figure 2, we present the estimated coefficient $\hat{\beta}_t$ for this outcome variable from the event-study specification (eq. 1). As shown, there are no pre-trends, and the decline in BTF as a proportion of total transport expenditure remains consistent over time. Similarly, the share of BTF in total household expenditure declined by 0.2 percentage points, which is small but statistically significant at the 5% significance level (column 4). In Appendix Figure E4, we display the event study graphs for the other three outcome variables from Table 2, namely: BTF and overall transport expenditures, and BTF as a share of total household expenditure. We find no evidence of pre-trends.

Additionally, we conduct an analysis at the HR level by aggregating household expenditure data and applying the SDID method using three different inference methods: bootstrap, jackknife, and placebo.[16] This allows us to assess whether the results align with the weighted regression analysis. The results (Appendix Table F7) are statistically similar to our baseline estimates in Table 2, though slightly larger in magnitude.

5.2 Evidence from the Delhi Primary Survey

We next utilize the sample from the Delhi Primary Survey to examine changes in monthly expenditure on all types of transportation, including bus expenses, at the *individual* level.[17] Among non-users, 64% spent between ₹1 and ₹1,000 per month on transportation, and the remaining respondents spent more than ₹1,000. Among users, both new and continuous, 55% reported zero monthly spending on transportation, including buses, in the post-program period. The remaining 45% spent between ₹1 and ₹1,000. Specifically, among *new bus users* (see Figure 3), 82% spent more than ₹1,000 per month on transportation before the program, but this figure dropped dramatically to 1% after the program was implemented. This 81-percentage-point difference is statistically significant at the 1% level. Furthermore, while none of the new bus users reported zero spending on transportation before the program (the ₹0 category in Figure 3), the proportion increased to 53% after the program. To the extent that the two user groups (new and continuous) are comparable, there is a notable shift in travel expenditure patterns, which complements

[16] Placebo inference is our least preferred method, as it relies on the assumption of homoscedasticity.

[17] The survey inquires about the monthly travel expenditures of all respondents after the launch of the *Pink Slip* program in Delhi. However, it asks only new bus users about their monthly travel expenditures before the program's launch; that is, for new bus users, the survey records expenditures both before and after the program.

the household-level results presented above.[18]

In interpreting the treatment effect, we note that if paid bus ridership was widespread among women prior to the policy, the eliminated fare would directly reduce their expenditures. The Delhi Survey, however, documents the presence of a large segment of new users following the introduction of the policy. For these women, free bus ridership may imply new travel demand or a substitution from other modes of transport. Either of these changes is likely to impact time use, which we will discuss in the next section.

5.3 Evidence from the CAG Survey

We further utilize the CAG survey to examine monthly savings from the free bus program for women in Tamil Nadu. We display the distribution of savings in Figure 4. The figure shows that 50% of respondents report saving between ₹401 and ₹1,500 per month, while a smaller share reported savings below ₹200 or above ₹1,500. These results are consistent with patterns observed in the Delhi Primary Survey and provide additional evidence of the importance of transport *affordability* for women.

We further examine ridership behavior and pricing using the CAG data. The average change in ridership is 0.75 trips per week. The pre-policy average daily expenditure on buses was ₹36.45. Our regression analysis shows that women are responsive to changes in the price of bus rides: a one standard deviation decrease in daily bus expenditure is associated with a 0.14 standard deviation increase in weekly bus trips. This result suggests that women's demand for bus rides is responsive to price changes. The details are in Appendix B.

6 Impact on Time Use

Our second set of main results concerns time use.[19] Overall, we find no statistically significant change in travel time or time spent on household chores when pooling all women. Because a very large share of women are out of the labor force, and travel time does not change for these women,[20] average travel time in the pooled sample remains unchanged (Appendix Table F8). To study intensive-margin effects on labor supply (hours worked), we focus on women in the labor force and examine whether the free bus scheme reduces

[18]The magnitudes of savings vary across datasets as the primary surveys are targeted to bus riders with the caveat that they are not representative, and the household survey results are not conditional on ridership as this data does not collect bus ridership information.

[19]To reiterate, the CPHS reports daily time spent on household chores and travel time (without breaking down by motive for travel or by mode), and for employed women, time spent in work.

[20]In May-August 2020, there were 89.5% of women reported being out of the labor force in the data.

their travel time and how any time savings are reallocated between work and household chores. In Section 8, we show that there is no change in employment on the extensive margin.

We first assess the impact of the policy by baseline employment status of women. As mentioned in the data section, we do not observe all women in all periods. Hence, the employment status is based on the last pre-policy period they were in the sample. Utilizing the richness of our data and sample size, we then document time-use changes among such employed women by education level and marriage status. During our study period, among 213,857 women, 73.5% are married, 6.4% are employed at baseline, and 4.4% are both employed at baseline and married. Subsequently, we present a simple model of intra-household time allocation consistent with our findings. We also assess its implications on men's time use. Then, we document the findings for the women who were unemployed at baseline.

6.1 Time Use of Employed Women

All Employed Women We estimate equation (2) for women employed in the baseline, i.e., reported working in the last pre-policy period they were surveyed. We present the results for the time devoted to travel and leisure for these women. Subsequently, we examine the extensive margin of being in the labor force as some of these women can transition out of the labor force, followed by intensive margin effects on hours worked.[21] The results are reported in panel A of Table 3.

As shown in column 1, employed women in treated states spent less time traveling after the implementation of the free bus program compared to those in control states. This is consistent with a potential substitution from slower modes of travel, such as walking or cheaper but slower buses, to faster buses. The time saved from reduced travel can be reallocated to household chores, additional work, or a combination of both. We find evidence of both: since the dependent variable is in terms of hours, the estimated coefficients imply that time spent on domestic tasks (column 2) increased by 11 minutes per day ($0.183 \times 60 = 10.98$). In column 3, we check the extensive margin for exits from the labor force—relevant because such women are coded as missing in our intensive margin analysis—and find no statistically significant effect, indicating that selection does not drive our results. Finally, on the intensive margin, we show that the time spent working

[21]Hours worked when an individual is not in the labor force are coded as missing regardless of period or gender when conducting the intensive margin analysis.

(column 4) increased by 6.8 minutes per day ($0.114 \times 60 = 6.8$).[22] The labor supply increases by 1.5% of pre-policy mean hours and is only 0.06 of a standard deviation (SD).[23] We also show the corresponding event study graphs for time use in Appendix Figure E5. We do not find evidence of pre-trends.

Employed Women by Education We next explore if this pattern across employed women changes by education. We classify women with no education beyond primary school as low-education, those who have attended middle, secondary, or higher secondary school as medium-education, and those holding a bachelor's degree or higher as high-education. We document the results by education level in Panel B of Table 3.[24]

Among highly educated employed women, we find no statistically significant effect on travel time. However, they increase time spend on work by 16 minutes per day ($p < 0.01$) and reduce time spent on household chores by 14 minutes per day, although the latter effect is not statistically significant at conventional levels. In contrast, among women with low levels of education, we observe a reallocation of time savings from travel to both household chores and work (the sum of the estimated coefficients TP + TPL in Table 3).[25] Finally, among women with medium levels of education, we observe a reallocation of time savings from travel towards household chores, accompanied by a reduction in time spent working (the sum of the estimated coefficients TP + TPM in Table 3). As in Panel A, column 3 shows that there is an insignificant transition to being out of the labor force.[26]

Employed Women by Marital Status Household dynamics between married couples might result in differences in how women time savings are reallocated. In India, as in many other developing countries, social norms ascribe responsibilities such as child-rearing and cooking to women. These gender-based expectations may affect married and

[22]The number of observations varies across outcomes in Table 3 because travel time and time spent on household chores are observed for all women employed at baseline, including those who were out of the labor force in other survey periods, but labor supply hours are missing for such individuals. In Appendix Table F9, we report results that exclude these observations for travel time and household chores as well to assess the sensitivity of our findings for a consistent set of observations. The results are both quantitatively and qualitatively similar to those reported in Table 3.

[23]The SD of time spent on work for women employed at baseline is 1.94.

[24]These results are based on women's education levels before the program's implementation. As shown in Appendix Table F10, changes in education status from the pre- to post-period are negligible.

[25]The difference between high- and low-educated women in terms of daily travel time might be due to the latter (low-earning) switching their mode of transport from walking to free buses, while the former (high-earning) already using buses before the program. However, our data does not allow us to parse this out completely.

[26]The null extensive margin effect reassuringly demonstrates that the work hours on the intensive margin are not biased due to selection.

unmarried employed women differently. Hence, we explore whether marital status influences how women reallocate their time. We present the results for employed women by marital status in Panel A of Table 4. We find that, after the program's implementation, employed married women in treated states saved 16 more minutes on commuting per day compared to unmarried counterparts (column 1 of Panel A in Table 4).[27] They not only substituted this saved time towards household chores, they also reduced their labor hours. On the other hand, unmarried women substitute the time saved to increase their working time by 0.43 hours. This is a 5.8% increase over pre-policy mean and 0.22 of a SD. They also reduce the time devoted to household chores significantly to increase their labor supply. These results imply that unmarried women employed at baseline were able to increase labor supply on the intensive margin and benefit from the program. The overall increase in labor supply for women employed at baseline reported above (column 4 of Table 3) is driven by unmarried employed women, while the smaller magnitude arises from the offsetting effect of the reduction in labor supply for married women.

In Panel B of Table 4, we restrict the sample to employed married women and find similar results to those in Panel A: on average, employed married women in treated states spent 19 minutes less on travel per day compared to those in control states,[28] 44 minutes more on domestic tasks, and 23 minutes less on work compared to their counterparts in control states after the program's implementation. In Figure 5, we present the event study graphs for this sample. As shown, we observe a consistent decrease in travel time, an increase in time spent on household activities, and a decrease in time spent on work, with no evidence of pre-trends.

Employed Married Women by Education Married women's educational status can affect their allocation of time between paid work and household production. Given the richness of our data, we are able to examine how the impacts on employed married women vary by education level. The results are reported in Table 5. In the triple interaction specification, highly educated employed married women serve as the excluded (reference) category. While the triple interaction terms capture differential effects by education group, we also compute the overall effect for each education category by summing the relevant double and triple interaction coefficients and reporting their associated standard

[27]The results are based on women's current marital status, but are robust to using pre-period status. As shown in Appendix Table F11, approximately 97% of women retained the same marital status in the post-period.

[28]We use the opportunity cost of time, i.e., wages, to determine the value of time saved on travel. Assuming the women work 20 days in a month, and using the pre-policy average wage for this sample, this amounts to ₹602 saved per woman per month. This amount is equivalent to 11% of their household food expenditure in the pre-policy period.

errors and p-values at the bottom of the table.

In column (1), we find that, after the program's implementation, low-educated and medium-educated married women in treated states reduced their travel time by 24 and 17 minutes, respectively, compared to those in control states. Column (3) shows the effects on work time: compared to highly educated married women, those with low and medium levels of education substantially reduced their labor supply. The triple-interaction estimates indicate a relative daily reduction in work time of 28 minutes for low-educated women and 20 minutes for medium-educated women, although neither estimate is statistically significant at conventional levels. The overall effects, reported at the bottom of the table, show a 31-minute reduction ($p < 0.01$) for low-educated and a 23-minute reduction ($p < 0.01$) for medium-educated married women. Most of the reductions in travel and work time were redirected toward domestic tasks, resulting in a 45-minute increase for low-educated and a 51-minute increase for medium-educated married women. For high-educated married women, we find no statistically significant reduction in work time or increase in household chores; however, we do observe an 11-minute reduction in travel time.

Our analysis indicates that the disproportionately large burden of household work on married women precludes them from fully benefiting in the labor market by working more hours. Instead, women use the time saved from commuting to increase time spent on household work, potentially supporting the labor supply of spouses and other men in the household. We examine this mechanism formally in the following section on husbands' time allocation. We interpret this result as gender roles within households undermining the potential positive effects of the program on female labor market outcomes. The following subsection formalizes this mechanism through a simple model of optimal time allocation within the household and highlights the assumptions under which the model is consistent with the empirical findings.

6.2 A Model of Intra-Household Time Allocation

Our goal is to present a proof-of-concept showing a plausible economic explanation for the finding that low- and medium-educated married women reduce their work time while increasing time spent on household chores. We aim to characterize the conditions under which the model is consistent with our empirical findings and whether there are additional empirical implications that follow from it.[29]

For the purposes of this exercise, we consider couples with non-high-educated women

[29] We do not claim that this is the sole mechanism at play, nor do we rule out alternative explanations.

(capturing both low- and medium-educated categories) and simply label them as low-educated. In the model, decision-making at the household level aims at maximizing joint utility in the presence of a nonmarketable household good and a joint labor supply decision (Chiappori, 1997). The key insight is that household task allocation responds to changes in transportation costs. When free bus rides reduce women's pecuniary travel costs to zero, tasks that combine fixed time requirements with necessary travel components—like school runs and grocery shopping—become more efficiently allocated to women rather than men. The gender wage gap increases the likelihood of such re-optimization at the household level, as men typically earn more than women within the same household.[30]

Consider a two-person household consisting of a male (m) and female (f), each endowed with E units of time (hours). There exists an indivisible household chore that must be completed by exactly one household member. For simplicity, we focus on this single task, which represents the type of household work that may be reallocated following the introduction of a subsidy program, for example, work such as grocery or school runs, which involve travel. While our model considers only one chore, additional household tasks could be incorporated to account for the empirical observation that women typically allocate more time to domestic activities than men, both before and after the program.

The chore requires H hours to complete (invariant across performers) and T_j^H hours of travel time, where $j \in m, f$ indexes the performing spouse. Travel time for the chore may differ across spouses if they take different modes, such as walking versus public transit. Similarly, commuting takes a gender-specific time T_j^W. The spouse performing the chore works in the remaining time, $h_j = E - H - T_j^H - T_j^W$, while the other spouse works for $E - T_{-j}^W$ hours. They earn an hourly wage of $w_j > 0$. The chore has a fixed and marginal disutility, both of which are gender specific. The marginal disutility C_j is per travel time, which also applies to commuting. Total disutility from the chore is then $D_j + C_j T_j^H$. In what follows, we assume that there is a gender wage gap, $w_f < w_m$, and that the fixed cost of the chore is possibly lower for the female, $D_f \leq D_m$, capturing either non-pecuniary cultural factors or the comparative advantage of women in such tasks. On the other hand, the marginal travel cost is higher for the female, $C_f > C_m$, capturing the physically demanding nature of tasks such as carrying groceries or potential harassment

[30] We use the PoI section data to identify husbands and wives and the InP section data to determine individuals' average monthly wages between January and March 2021, the three months before the program's implementation. In this matched sample with income observations, about 99% of the households reported the husband's wage as being higher than or equal to the wife's. In these households, husbands' wages are, on average, *twice* as high as their wives.

that women may endure while traveling.

The household maximizes total income net of disutility:

$$U = \begin{cases} w_m[E - H - T_m^H - T_m^W] + w_f(E - T_f^W) - (D_m + C_m T_m^H) - C_f T_f^W - C_m T_m^W & \text{if } m \text{ does the chore,} \\ w_f[E - H - T_f^H - T_f^W] + w_m(E - T_m^W) - (D_f + C_f T_f^H) - C_f T_f^W - C_m T_m^W & \text{if } f \text{ does the chore.} \end{cases}$$

Before the female travel subsidy, both spouses find it optimal for the household to take the slower mode of transport (walking) so that $T_f^H = T_m^H = \overline{T}^H$ and $T_f^W = T_m^W = \overline{T}^W$. This assumption is without loss of generality, as our focus is on the *change* in travel times rather than their initial *levels*. The only requirement is that the travel cost changes for women relative to men. In the initial allocation, the husband performs the chore if

$$\underbrace{(C_f - C_m)\overline{T}^H}_{\substack{\text{Female travel}\\ \text{penalty}}} > \underbrace{(w_m - w_f)(H + \overline{T}^H)}_{\text{Foregone income}} + \underbrace{(D_m - D_f)}_{\substack{\text{Male fixed}\\ \text{disutility penalty}}},$$

that is, if the female travel penalty is sufficiently high relative to the opportunity cost $(w_m - w_f)(H + \overline{T}^H)$ of female labor supply plus the incremental male fixed disutility.

After the subsidy, women's travel times decrease to $T_f^H < \overline{T}^H$ and $T_f^W < \overline{T}^W$ (e.g., due to the travel subsidy, she can ride the bus rather than walking), men's remain at the initial higher values. It is straightforward to show that the household chore will be reallocated from the male to the female partner if there is a large enough drop in travel time to T_f^H:

$$\frac{(w_m - w_f)H + (D_m - D_f) + (w_m + C_m)\overline{T}^H}{w_f + C_f} > T_f^H,$$

where our initial assumptions guarantee that the left-hand side of this inequality is positive. Rearranging terms for ease of interpretation, we obtain

$$\underbrace{(w_m - w_f)(H + \overline{T}^H)}_{\text{Income gain}} + \underbrace{w_f(\overline{T}^H - T_f^H)}_{\text{Time savings}} + \underbrace{D_m + C_m\overline{T}^H}_{\text{Male utility gain}} > \underbrace{D_f + C_f T_f^H}_{\text{Female disutility cost}}.$$

This condition states that for the female partner to take on the household chore (allowing the male partner to increase work hours), the combined benefits—the sum of net household income gain from reallocation, the woman's time savings from the subsidy, and the man's utility gain—must exceed the woman's disutility from performing the chore.

As expected, commute times do not appear in these household task allocation rules. They matter, however, in interpreting the overall reduction in female travel times. On the one hand, the wife's travel time decreases from time savings in commuting. On the other hand, she assumes the household chore with a travel component. If the former drop dominates the latter increase, total female travel time decreases:

$$\overline{T}^{W} - T_f^{W} > T_f^{H},$$

which is a plausible assumption since commuting typically involves a longer trip.

To sum up, three assumptions are sufficient to rationalize the estimated reallocation of chores within the household: a gender wage gap favoring men, the indivisibility of a high enough time required for essential household work, and asymmetric gender-specific disutility for these chores. These are likely to apply to households with less educated, low-wage women, consistent with empirical evidence as documented above and in recent literature (Fletcher et al., 2017). Under these plausible assumptions, the model offers a useful lens through which the empirical results obtained so far can be interpreted.

Testing Model Implications for Time Use of Husbands In our model, employed husbands of low-educated women take on a reduced share of household responsibilities, reduce their travel time, and increase work time. We test these implications using the CPHS data,[31] and present the results in Table 6. In order to assess husbands' contribution to total household work time, we look at the share of time spent by the husband in the total time the couple spends on household chores. Employed husbands reduce their share across all spousal education levels (column 1), especially for those married to low- and medium-educated working women. In addition, travel time decreases for employed husbands across all spousal education levels (column 2), possibly reflecting fewer trips that could be complementary with household chores, such as accompanying minor kids' trips to/from school or going to a grocery store. This result is consistent with the model's implications for intra-household time reallocation of chores.[32]

Finally, husbands of medium-educated women, who account for 55.6% of couples with an employed low- or medium-educated woman, significantly increase their work hours (column 3); husbands of low-educated women show no such response.

[31] We are able to match 87% of employed married women to husbands, resulting in a smaller number of observations in Table 6 relative to Table 5. 92% of the men in the matched sample are employed.

[32] In the stylized model, total time spent on household chores is constant. We therefore emphasize the results in terms of husbands' *share* of time, which better map to the model. In terms of levels, we find no effect on time spent on household chores (3.6 minutes, p-value $= 0.69$) for employed husbands married to highly educated employed women. In contrast, employed husbands married to low- and medium-educated employed women increase that time by 15.1 and 8.7 minutes (both p-value < 0.01), respectively.

6.3 Impact on Time Use for Unemployed Women

To complete our analysis of time use, we shift our focus to examining the effects for women unemployed at baseline. Table 7 summarizes the results. While we find a null effect on travel time, we observe that unemployed women in treated states spend 1.6 fewer hours on domestic duties compared to their counterparts in control states following the implementation of the *Pink Slip* program. We also present the corresponding event study graphs in Appendix Figures E8a and E8b, which show the dynamic effects over time. Specifically, in Appendix Figure E8b, we observe a consistent reduction in time spent on household chores in the post-treatment periods, with no evidence of pre-trends. The time saved from domestic tasks may have been used for leisure activities or reallocated to job search efforts. While the PoI data does not include a variable for time spent on job search-related activities, it provides information on time spent on leisure, which includes time spent on outdoor sports, socializing with friends, and indoor entertainment. We find no statistically significant increase in leisure time.

7 Impact on Food Expenditures

One of the surprising results of our empirical analysis so far is the reduction in work time by employed married women (Table 4). In the model, we present a non-pecuniary mechanism, i.e., the disutility of travel and the relative difference in it for wives and husbands. According to that mechanism, joint household welfare increases through the reallocation of chores from men to women. As the variable disutility of travel drops asymmetrically for women, savings from shopping for cheaper groceries in distant locations are another potential benefit. While we excluded this pecuniary mechanism from the model, our framework still predicts that women use free buses to take on more household responsibilities, such as grocery shopping. This shift in behavior suggests potential financial benefits as well, either through reduced travel costs or improved access to more affordable goods that were previously out of reach. These savings are likely to be important in a developing country context where food expenditures constitute a high share of expenditures for low-educated households.

In order to shed light on this potential benefit, we examine whether food expenditure falls for households with married employed women. The results are presented in Table 8. Panel A reports estimates for monthly household expenditure on food, while Panel B displays estimates for food expenditure as a share of total household expenditure. Columns 1 to 4 present results for households with married employed women of varying education levels. In Panel A, we find that while the decline in food spending occurs across all education levels, the largest reduction is observed among households with medium-educated employed married women (column 3). In Panel B, we find that food expenditure shares held steady for households of low- and medium-educated women, due to a decrease in total expenditures by an amount similar to the reduction in food expenditure (columns 2 and 3 in Panel A of Appendix Table F13). On the other hand, households of highly educated employed married women decreased their food expenditure *share* by 3.7 percentage points (column 4), explained by both a decrease in food expenditures (panel A) and an increasing level of total household expenditures (column 4 in Panel A of Appendix Table F13).[33] This decreased share of food in total expenditures, a widely used measure of standard of living (Chai and Moneta, 2010), suggests a possible increase in the welfare of households with highly educated employed wives.

Assuming groceries are a normal good, such that consumption rises with income, a decline in grocery expenditure is more plausibly attributed to a reduction in the effective price paid by households than to a decrease in the quantity consumed. Consistent with this interpretation, suggestive evidence from the CAG survey indicates that savings from access to free bus travel are partially redirected toward food expenditure (Appendix Figure E7). Nevertheless, even after accounting for this increase, we observe a statistically significant net decline in total grocery spending, plausibly driven by access to lower-priced goods. We conjecture that this decline reflects women's increased mobility, which enables them to shop at more affordable markets located farther from home.

A notable observation is that low- and medium-educated women are reducing their labor supply to increase time spent on household chores. These women face the trade-off between increasing their income by supplying extra labor versus saving on food expenditure. Our results demonstrate that the women choose the latter. We verify that the increase in earnings from supplying labor is less than the savings accrued from a reduction in food costs for households with low-educated employed wives. Among these households, we observe a ₹571 reduction in monthly food expenditure (column 2 of Panel A in Table 8). On the other hand, these women reduced their work time by 31 minutes per day. Given their average pre-period monthly wage of ₹4,340, and assuming an 8-

[33] As a robustness check, we exclude the Delta wave and present the results in Appendix Table F12, which are largely similar to our baseline estimates. We also examine the impact on household food expenditure for all households with women in Appendix Table F14, and find a decline across the board. Specifically, the food expenditure share decreased by 1.2 percentage points for treated households relative to control households following the program's implementation. These results are also robust to the exclusion of the Delta wave. In Appendix Figure E6, we present the corresponding event study graphs for monthly food expenditure (corresponding to Column 1 in Appendix Table F14) and the food expenditure share (corresponding to Column 3 in Appendix Table F14), and find no evidence of pre-trends.

hour workday with 20 workdays per month, the total monthly forgone wage amounts to ₹270. Meanwhile, there is no significant change in their employed husbands' work time. Despite that, the overall household savings from reduced food expenditure are greater than the wage income foregone. This substantial difference in pecuniary benefits from increasing household work tilts the decision of the low-educated women and their husbands towards using women's time towards household chores (i.e., possibly grocery shopping from farther than before) without altering men's labor supply.[34] Turning to households with medium-education employed wives, we find a 23-minute daily reduction in women's work time. With an average monthly wage of ₹7,399, and assuming an 8-hour workday with 20 workdays per month, this implies a forgone income of ₹355, which is smaller than the food savings of ₹911 (column 3 of Panel A in Table 8). At the same time, their husbands increased their work time by 12 minutes per day. With an average pre-period monthly wage of ₹10,992, and assuming an 8-hour workday with 20 workdays per month, this translates to an additional income of ₹271. Accounting for both spouses' labor adjustments, the net household gain exceeds the wife's forgone earnings, reinforcing the model's prediction of intra-household labor reallocation.[35]

A complete welfare analysis, which is beyond the scope of our paper, would have to consider the net change in total producer surplus, as nearby sellers may lose market share while those farther away gain customers due to the policy intervention. Also, we do not have data on health outcomes or calorie consumption to assess how these savings might translate into improved development outcomes.

8 Impact on Employment and Job Search

Employment Changes and Job Search Behavior: CPHS Data We estimate equation (2) to investigate whether women are more likely to be in the labor market, more likely to be employed, and more likely to switch from being out of the labor market to actively searching for jobs after the *Pink Slip* program. The results are reported in Panel A of Appendix Table F15. We find no statistically or economically significant impact on any of these outcomes. We also present the corresponding event study graphs in Appendix Figure E9, which show no evidence of pre-trends for these four outcome variables.

[34] Although the model does not incorporate leisure, we do find an increase in the leisure of the husbands of these women. The estimated total effect on leisure of employed husbands of low-educated employed wives is 0.54 and is statistically significant at the 1% level.

[35] We find that husbands' leisure time increases: the estimated total effect for employed husbands of medium-educated employed wives is 0.27 and statistically significant. We also find that the husbands increase their labor supply to compensate for the reduced labor supply of their wives.

However, when we analyze the effects by marital status, we find a marginal increase in job search activity among married women (column 4 of Panel B in Appendix Table F15). Specifically, married women in treated states who were previously out of the labor market are 0.8% more likely ($p < 0.05$) to start actively searching for jobs after the program's implementation compared to their counterparts in control states. According to the 2011 Census, there were about 223 mn married women in India. Given that 74.5% of women do participate in the labor force, a 0.8 percentage point increase implies that, if implemented nationwide, the program could induce approximately 1.3 million married women to transition from non-participation to active job search (223 million $\times$ 0.745 $\times$ 0.008) These findings suggest that while the program does not lead to an immediate increase in employment, it encourages women, particularly married women, to enter the job search process. In the long run, this could potentially lead to higher employment. This finding is consistent with recent evidence from China, which shows that an extra minute of commuting time lowers married women's labor force participation by 0.5 percentage points (Liu et al., 2025).

8.1 Traveling in Search of Work- Delhi Survey

The Delhi Survey reports the purpose of travel and the average travel distance for each respondent (new and existing riders) in the post-implementation period. We use this data to provide suggestive evidence that free passes enable women to travel greater distances, potentially allowing them to work in more remote jobs or facilitating their job search efforts. We compare the purpose of travel and the average travel distance between new and continuous bus transit users in the post-implementation periods.[36] We acknowledge that the new users are induced to use the buses because they are free and hence are selected relative to incumbent users. To address this, we match the comparison group of continuous users on observable characteristics to the new users (discussed in Section 3.2.1). While this does not address the selection issue entirely, this comparison is still revealing and valuable. With this caveat, we estimate the following regression:

$$Y_i = \beta \ I_{\text{new users}} + X_i + \epsilon_i, \tag{3}$$

where Y_i is a dummy variable for travel purposes, which is equal to one if it is for work, or a dummy variable for average travel distance via buses, which is equal to one if the average distance exceeds 10 kilometers. $I_{\text{new users}}$ is a dummy variable set to one for

[36]Information on pre-program travel distances is available only for new users, not incumbent users. Hence, we are not able to use the pre-period data

new users and zero for continuous users. X is a vector of control variables, including an individual's marital status and education level. The results are reported in Table 9.

In column 1, new bus users are 6.8% more likely to travel for work than continuous users. The estimated coefficient decreases slightly to 6.6% after conditioning on marital status and education. In columns 3 and 4, we observe that, on average, new users are 18.2%-19.8% more likely to travel longer than 10 kilometers than continuous users. This suggestive evidence indicates that the free bus program enables unemployed women to search for jobs. Thus, it is possible that in long run, it improves the employment rate.

8.2 Change in Ridership Among Unemployed- CAG Survey

We further leverage the CAG survey to examine changes in bus ridership among unemployed women. Figure 6 displays the distribution of bus use among unemployed female users aged 18–50 before and after the introduction of the free bus program, showing a clear rightward shift. Among those who used buses fewer than two times per week prior to the program, 60% increased their usage to more than two times per week. Similarly, 17% of those who previously used buses 2–4 times per week began using buses more than five times per week. These descriptive patterns support the idea that the free bus program encouraged greater mobility among unemployed women, potentially for expanded job search.

9 Cost-Benefit Analysis

We conduct a back-of-the-envelope cost-benefit analysis to assess whether the benefits of the *Pink Slip* program outweigh its fiscal costs, with the details provided in Appendix C. On the cost side, we estimate the total annual program expenditure to be approximately ₹31.1 billion for Tamil Nadu and Punjab combined. This includes ₹28.3 billion in direct reimbursements (based on official ridership and an assumed cost of ₹16 per ride) and an additional 10% to account for administrative and implementation overheads.

On the benefit side, we consider both labor market outcomes and household consumption savings. In terms of labor supply, we had estimated that employed unmarried women increase their work time by 26 minutes per day. Assuming that they all use free buses and work 240 days per year, annual wage gains amount to ₹10.4 billion. In contrast, employed married women, particularly those with low and medium education, reduce their work time following the program. Using the same 240-day assumption for married women, and accounting for their wage losses offset by their husbands' increased work time, we estimate a net labor market benefit of ₹0.35 billion annually.

A more substantial source of benefit arises from household savings in food expenditure. We estimate that eligible households save approximately ₹504 per month on food costs, which we interpret as a price effect rather than a reduction in consumption. Aggregated across eligible households in the two states, this results in total annual food expenditure savings of approximately ₹124.5 billion. Admittedly, some of this expenditure shift comes at the expense of high-price sellers who lose business. On the other hand, there may be additional gains to the extent that lower traveling costs increase competition across food vendors and lower their markups. Such general equilibrium effects are beyond the scope of our analysis.

Combining labor and consumption benefits, the program yields an estimated net benefit of roughly ₹94 billion per year (₹124.5+₹0.35-₹31.1), far exceeding its cost. Aside from general equilibrium impacts mentioned above, this may be a lower-bound estimate, as it excludes unquantified benefits such as improved safety, greater autonomy, and household productivity.

10 Robustness Checks

We perform five robustness checks to validate our findings. Specifically, we replicate our main results on household monthly transport expenditure and on employed married women, as presented in Table 2, Panel B of Table 4, and Table 5. Since we derive object weights from the SDID method at the HR level, we first assess whether clustering standard errors at the HR level affects statistical inference. We present the results in Appendix D.1. In some cases, statistical significance is reduced—for example, in column 1 of Table D3, the coefficients on travel time for the double and triple interaction terms lose significance. However, the combined effect of these terms remains statistically significant. Nonetheless, most of our main estimates remain statistically significant at conventional levels under this alternative clustering approach.

Second, to evaluate the reliability of our statistical inference given the uncertainty in SDID weights, we apply the jackknife algorithm proposed by Arkhangelsky et al. (2021).[37] We iteratively drop all observations from one HR at a time and re-estimate our DID regression using the remaining data. The jackknife variance is calculated using the formula proposed in Arkhangelsky et al. (2021), $\hat{V}^{jack} = \frac{95}{96}\sum_{i=1}^{96}\left(\hat{\tau}_{-i} - \hat{\tau}\right)^2$, where $\hat{\tau}_{-i}$

[37] We did not apply either the bootstrap or placebo procedures proposed in Arkhangelsky et al. (2021), as the former is computationally intensive in our setting, and the latter relies on the assumption of homoskedastic standard errors.

is the estimated treatment effect when observations in HR i are excluded. We report the results in Appendix Tables D4 and D5. Columns 3 and 5 present the baseline and jackknife p-values, respectively. For household transportation expenditures, the estimates remain statistically significant at conventional levels (Table D4). Among employed married women, we observe a consistently significant reduction in travel time and an increase in time spent on household chores (Panel A of Table D5). The results for low- and medium-educated employed married women are mostly statistically significant at conventional levels (Panel B of Table D5). These results further reinforce the robustness of our main findings.

Third, to address a concern that women over 50 may have already retired, we restrict the sample to women aged 15–49. This age range is also consistent with the one used by the National Family Health Survey. The findings, presented in Appendix D.3, confirm the robustness of our results within this subgroup. Fourth, another concern might be that differences in COVID-19 regulation stringency measures across treatment and control groups could drive changes in household expenditures. Although we have controlled for COVID-19 cases in our main specification, as a robustness check, we additionally control for the share of days the state government had either recommended or required closing public transport in a month and the share of days the state government had either recommended or required individuals not to leave their house in a month. The results, presented in Appendix D.4, show that the estimated coefficients remain robust, with magnitudes and standard errors similar to those in our main findings.

Lastly, a related concern is that observed changes in travel time and BTF expenditure are driven by COVID-19 rather than the policy (Deshpande, 2022). To address this, we replicate our analysis while excluding periods corresponding to the peak of the Delta wave in India. Specifically, in the household consumption analysis, we drop the first two post-treatment periods, while in the time usage analysis, we exclude the first post-treatment wave. The results, reported in Appendix D.5, show that although the estimated effects on household transportation expenditure attenuate slightly, they remain statistically significant. Additionally, the results on time use for employed married women persist, further reinforcing the robustness of our findings.

11 Conclusion

In response to extensive literature documenting how increased commuting costs reduce women's work hours and labor force participation, policymakers are increasingly focused on eliminating transportation barriers for women. This paper evaluates the *Pink*

Slip program—which provides free bus services to women across several Indian states—to assess how reduced commuting costs affect women's time allocation, including work hours, travel time, household responsibilities, and overall labor force participation.

Employing a synthetic difference-in-differences approach, we find that household expenditures on buses fall, and travel time for women employed before the program decreases. We also show, however, that reducing commuting costs alone may not be enough for women to increase work hours or participation in the labor market. Heterogeneous responses reflect the re-optimization of agents with varying demographic status: free buses incentivize unmarried women to increase their working hours. However, low- and medium-educated employed married women use the time saved from commuting to do more household work. These results highlight the potential importance of household-level decision-making in determining gender norms that impede the most vulnerable women from taking advantage of the free bus program to increase their labor supply.

Examining employment and job search outcomes, we find that while the *Pink Slip* program does not produce immediate increases in overall female employment, it facilitates job search, particularly among married women. Married women previously out of the labor force are 0.8% more likely to begin actively searching for jobs following program implementation. Evidence from the Delhi Primary Survey shows that new bus users are more likely to travel for work purposes and more likely to travel distances exceeding 10 kilometers compared to continuous users, suggesting the program enables access to more distant employment opportunities. These findings indicate that free public transportation removes mobility barriers to job search, potentially leading to longer-term employment gains even when immediate employment effects are not observed.

Further analysis suggests that the *Pink Slip* program's benefits extend beyond direct transportation savings to substantial household welfare gains through food expenditure reductions. Employed married women across all education levels decreased their food spending, with the largest reductions observed among medium-education women. We interpret these savings as resulting from women's enhanced mobility, enabling access to cheaper groceries at more distant locations. Crucially, for households with low-educated wives, the food expenditure savings outweigh the foregone wages from women's reduced work time, with no change in their spouses' labor supply. For households with medium-educated wives, savings from food expenditure are not larger than the foregone wages, so the husband increases his labor supply by a small amount. This suggests that the program's value extends beyond simple transportation cost reductions to enable household optimization strategies that generate net welfare gains, supporting our model's prediction of intra-household labor reallocation in response to asymmetric reduction in women's travel costs. That said, these women are not reaping the benefits associated with higher labor income in ways that are summarized in the review by Duflo (2012). In fact, contrary to that, they are induced to increase the time spent on household chores and reduce their labor income by working less. However, despite saving travel time, husbands enjoy more leisure or increase their labor supply just enough to offset the loss in women's income. To the extent that women's labor income empowers them, entrenched social norms tend to favor husbands in terms of time allocation.

Our findings have important policy implications: If the goal of providing free transportation to women is to improve women's labor market outcomes, only highly educated unmarried women show immediate gains, while low- and middle-educated employed married women reduce work hours. However, the program generates substantial broader benefits: household food expenditure savings, facilitation of job search among married women who were previously out of the labor market, and overall benefits that far exceed program costs, making it a beneficial intervention despite limited immediate labor market effects.

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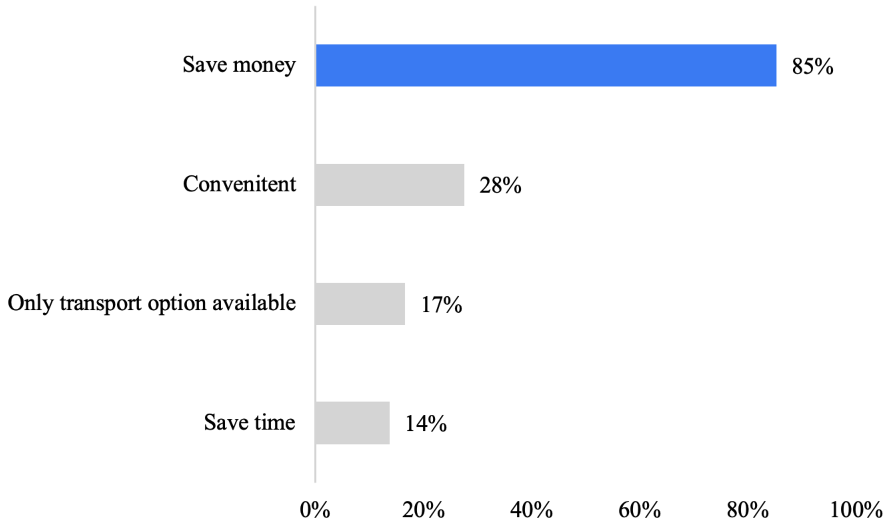
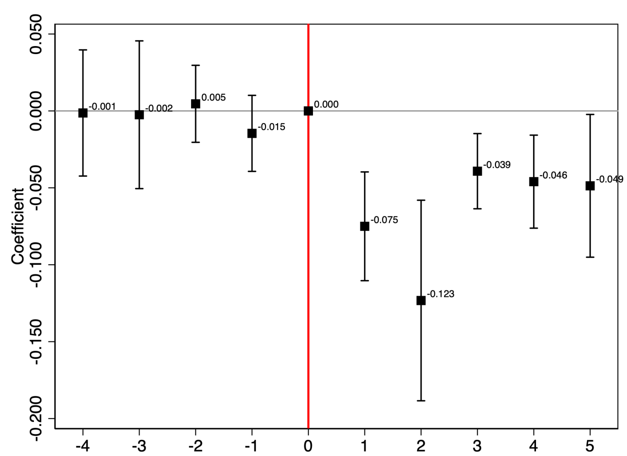
Figures

FIGURE 1: Top Four Reasons for Taking Free Buses (CAG Survey)



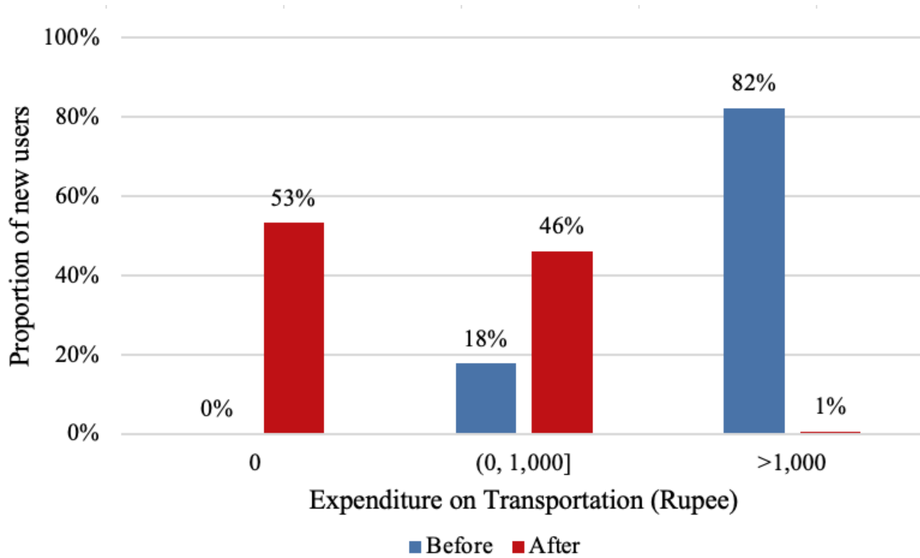
Notes: The survey data is from the Citizen Consumer and Civic Action Group (CAG) (Narayanan, 2024). The survey asked respondents why they chose to use free buses, and respondents could select multiple options. In this figure, we display the four most frequently selected reasons: saving money, convenience, being the only transport option available, and saving time. The sample is restricted to women aged 18–50.

FIGURE 2: Event Study Graph: BTF/Transport



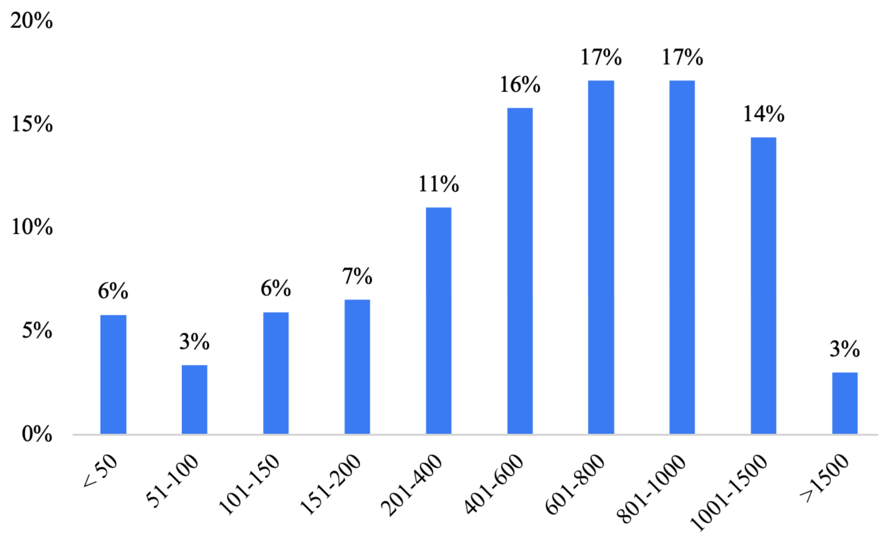
Notes: The outcome variable is the monthly household expenditure on daily bus, train, or ferry fares, expressed as a share of total monthly household transport expenditure. We analyze the sample of households that are also presented in the PoI data. The time unit of analysis is monthly, and $t = 0$ is one month before the program starts. The program started in April and May 2021 in Punjab and Tamil Nadu, respectively. The period of analysis is November 2020-August 2021 for Punjab and December 2020-September 2021 for Tamil Nadu. The regression includes household and month fixed effects and controls for the average number of daily new confirmed cases as a share of the population. Standard errors are clustered at the state level. Confidence intervals are at the 95 percent level.

FIGURE 3: Monthly Transport Expenditures (₹) Before & After the Program (Delhi Primary Survey)



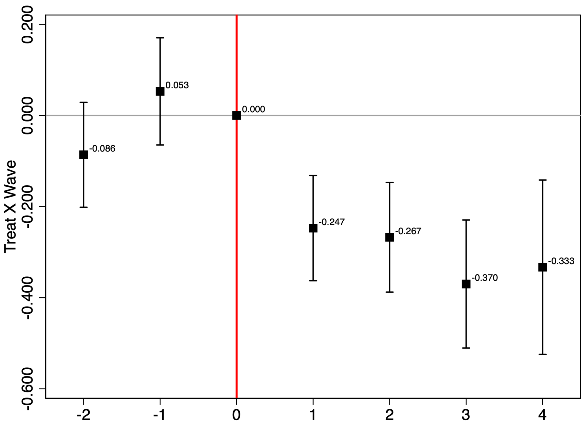
Notes: The figure plots the distribution of monthly transportation expenditures for 180 new bus transit users before and after the program. A new user is defined as someone who did not use buses before the program but started doing so afterward. The unit is the Rupee. The blue bars represent the share of new users whose average monthly expenditure on *all other modes of* transportation *before* the program falls into specific categories, such as spending ₹0, spending between ₹1 and ₹1,000, and spending more than ₹1,000. The red bars represent the same for new users of bus transit *after* the program's introduction. It should be noted that the red bar for the "$(0, 1000]$" category is positive because some new users still incur costs for other modes of transportation that are not free in the post-policy periods.

FIGURE 4: Monthly Savings from the Free Bus Program (CAG Survey)

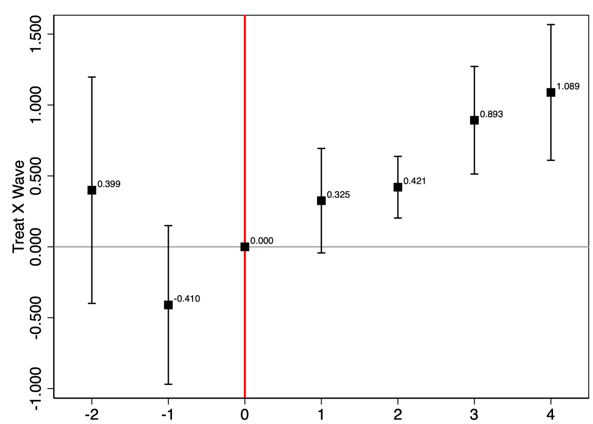


Notes: The survey data are from the Citizen Consumer and Civic Action Group (CAG) (Narayanan, 2024). Respondents were asked, "How much did you save on a monthly basis because of the free bus program?" and were given multiple categorical options to choose from, including: less than ₹50, ₹51–₹100, ₹101–₹150, ₹151–₹200, ₹201–₹400, ₹401–₹600, ₹601–₹800, ₹801–₹1000, ₹1001–₹1500, and more than ₹1500. In this figure, we display the distribution of reported monthly savings among women. The sample is restricted to women aged 18–50.

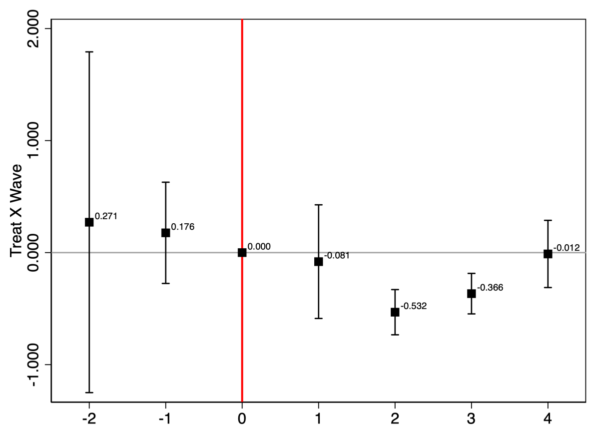
FIGURE 5: Event Study Graphs: Time Usage for Employed Married Women



(a) Travel Time



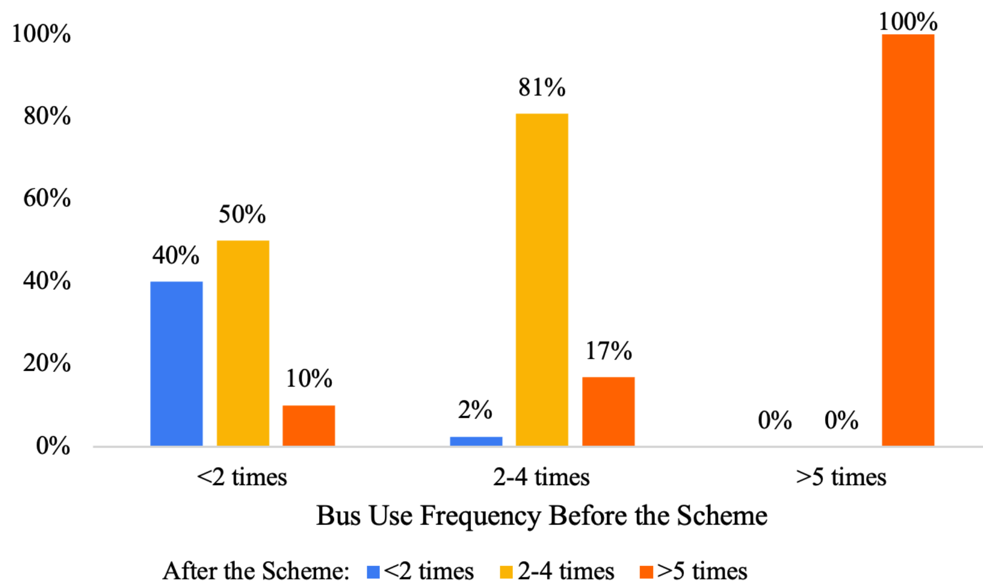
(b) Time for HH



(c) Time for Work

Notes: We restrict the sample to married women employed in the last pre-treatment period they are observed. Here, $t = 0$ represents one wave (four months) before the program. The program started in April and May 2021 in Punjab and Tamil Nadu, respectively. The time period of analysis here is May-August 2020 to May-August 2022 for both Punjab and Tamil Nadu. "Travel Time" = Time spent on travel. "Time for HH" = Time spent on household activities. "Time for Work" = Time spent on work done for the employer. All regressions include individual and wave fixed effects, as well as control for the average number of daily new confirmed cases as a share of the population. Standard errors are clustered at the state level. Confidence intervals are at the 95 percent level.

FIGURE 6: Weekly Bus Use Frequency Before and After the Program for Unemployed Women (CAG Survey)



Notes: The survey data is from the Citizen Consumer and Civic Action Group (Narayanan, 2024). In this figure, we show the distribution of weekly bus use frequency among unemployed female bus users aged 18–50, both before and after its implementation. The percentages should be interpreted as follows: for example, the first blue bar on the left indicates that 40% of women who took the bus fewer than two times per week before the program continued to do so after its implementation.

Tables

TABLE 1: User Perceptions of Buses & *Pink Slip* Program

	(1)		(2)		t-test
Variable	N	Mean/SD	N	Mean/SD	(1)-(2)/SE
Panel A. Non-users vs Users					
	Non-users		Users		Difference
Affordability and availability of free commute	184	3.196	1,106	3.914	-0.718***
		(0.786)		(0.820)	(0.065)
Safety against accidents, crashes, threats, and thefts	184	1.630	1,106	4.052	-2.422***
		(0.640)		(0.878)	(0.068)
Connectivity	184	2.772	1,106	4.046	-1.274***
		(0.798)		(0.919)	(0.072)
Bus frequency, waiting time, travel time, and unnecessary stops	184	2.484	1,106	3.238	-0.754***
		(0.992)		(1.197)	(0.093)
Accessibility to bus stops	184	2.424	1,106	3.167	-0.743***
		(1.053)		(1.091)	(0.086)
Panel B. New users vs continuous users					
	New users		Continuous users		Difference
Affordability and availability of free commute	182	4.071	924	3.883	0.189***
		(0.828)		(0.816)	(0.066)
Safety against accidents, crashes, threats, and thefts	182	3.945	924	4.073	-0.128*
		(0.884)		(0.876)	(0.071)
Connectivity	182	4.187	924	4.018	0.168**
		(0.878)		(0.924)	(0.074)
Bus frequency, waiting time, travel time, and unnecessary stops	182	3.214	924	3.242	-0.028
		(1.177)		(1.201)	(0.097)
Accessibility to bus stops	182	3.132	924	3.174	-0.042
		(1.048)		(1.100)	(0.089)

Notes: Respondents evaluate their perception of a particular aspect of buses on a scale ranging from 1 (highly unsatisfactory) to 5 (highly satisfactory). In the last column, we test the differences between treated and control areas using a t-test with equal variance. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

TABLE 2: The Impact on Household Transportation Expenditures

	(1) BTF	(2) Transport	(3) BTF/Transport	(4) BTF/Expenditure
Treat × Post	-25.882**	-48.507***	-0.060***	-0.002**
	(10.337)	(12.898)	(0.013)	(0.001)
HH FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Treated Mean	128.17	398.45	0.35	0.01
R^2	0.71	0.23	0.72	0.71
No. of HHs	115,745	115,745	115,745	115,745
N	785,868	785,868	785,868	785,868

Notes: We conduct analysis on the sample of households that are also represented in the individual data. "Transport" = Total monthly household expenditure on transport. "BTF" = Monthly household expenditure on daily bus/train/ferry fare. "Expenditure" = Total monthly household expenditure. All regressions include household and month fixed effects and control for the average number of daily new confirmed cases as a share of the population. The unit of outcome variables in columns 1-2 is Indian Rupees. The treated mean is the average for households in treated states and pre-periods. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

TABLE 3: Impact on Women Employed at Baseline

	(1) Travel Time	(2) Time for HH	(3) Out Labor Mkt.	(4) Time for Work
Panel A. Employed Women				
Treat × Post	-0.171***	0.183**	0.010	0.114*
	(0.029)	(0.088)	(0.021)	(0.056)
R^2	0.42	0.49	0.41	0.46
Panel B. Employed Women By Education				
Treat × Post (TP)	-0.075	-0.234	0.013	0.266***
	(0.052)	(0.164)	(0.020)	(0.092)
Treat × Post × Low-education (TPL)	-0.209***	0.641***	-0.010	-0.519***
	(0.048)	(0.202)	(0.025)	(0.141)
Treat × Post × Medium-education (TPM)	-0.066	0.419**	0.013	-0.032
	(0.053)	(0.181)	(0.017)	(0.110)
TP+TPL	-0.283***	0.407***	0.003	-0.253**
SE	(0.032)	(0.097)	(0.024)	(0.090)
p-value	[0.000]	[0.000]	[0.903]	[0.011]
TP+TPM	-0.141***	0.185*	0.025	0.234***
SE	(0.023)	(0.094)	(0.018)	(0.067)
p-value	[0.000]	[0.063]	[0.169]	[0.002]
R^2	0.42	0.49	0.41	0.47
Individual FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Treated Mean	0.63	3.01	0.09	7.34
No. of Individuals	11,454	11,454	11,454	11,454
N	56,436	56,436	56,436	47,718

Notes: In this table, we categorize women based on their employment status and education level during the pre-period, with employment defined as being employed in the last sampled period prior to the policy. The omitted group is the employed high-education women who have bachelor's degrees or above in panel B. "Travel Time" = Time spent on travel. "Time for HH" = Time spent on household activities. "Out Labor Mkt." = A dummy takes the value of one if a woman is unemployed and is neither willing nor looking for a job; it takes the value of zero if a woman is either employed or unemployed but is looking for a job (i.e., participating in the labor market). "Time for Work" = Time spent on work done for the employer. "Low-education" = Women who went to primary schools or received no education. "Medium-education" = Women who went to middle school, secondary schools, or higher secondary schools. All regressions include individual and quarter/wave fixed effects, as well as control for the average number of daily new confirmed cases as a share of the population. In columns 1,2 and 4, units are hours per day, and the treated mean is averaged over employed women in treated states during pre-periods. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is $p<0.1$, ** is $p<0.05$, and *** is $p<0.01$.

TABLE 4: Impact on Time Use Among Women Employed at Baseline, by Marital Status

	(1) Travel Time	(2) Time for HH	(3) Time for Work
Panel A. Employed Women by Marital Status			
Treat × Post (TP)	-0.037**	-0.175**	0.431***
	(0.016)	(0.076)	(0.044)
Treat × Post × Married (TPMa)	-0.261***	0.797***	-0.811***
	(0.039)	(0.089)	(0.122)
TP+TPMa	-0.298***	0.622***	-0.380***
SE	(0.043)	(0.117)	(0.116)
p-value	[0.000]	[0.000]	[0.004]
R^2	0.43	0.50	0.47
No. of Individuals	11,454	11,454	11,454
N	56,436	56,436	47,718
Panel B. Employed Married Women Only			
Treat × Post	-0.314***	0.729***	-0.385***
	(0.048)	(0.141)	(0.133)
R^2	0.45	0.49	0.51
No. of Individuals	7,035	7,035	7,035
N	34,028	34,028	27,812
Individual FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Treated Mean	0.70	3.20	7.32

Notes: In this table, we categorize women based on their employment status during the pre-period, with employment defined as being employed in the last sampled period prior to the policy. A woman is unmarried if she is divorced, unmarried, or widowed. The omitted group is employed unmarried women. "Travel Time" = Time spent on travel. "Time for HH" = Time spent on household activities. "Time for Work" = Time spent on work done for the employer. "Married" = A dummy takes the value of one if a woman is married and zero if the woman is divorced, unmarried, or widowed. All regressions include individual and quarter/wave fixed effects, as well as control for the average number of daily new confirmed cases as a share of the population. All units are hours per day. The treated mean is hours per day and is the average for employed married women in treated states during pre-periods in Panel B. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

TABLE 5: Impact on Time Use Among Married Women Employed at Baseline, by Education

	(1) Travel Time	(2) Time for HH	(3) Time for Work
Treat × Post (TP)	-0.175**	0.094	-0.049
	(0.065)	(0.159)	(0.319)
Treat × Post × Low-education (TPL)	-0.225***	0.663***	-0.467
	(0.061)	(0.145)	(0.315)
Treat × Post × Medium-education (TPM)	-0.107*	0.764***	-0.335
	(0.057)	(0.209)	(0.319)
TP+TPL	-0.399***	0.756***	-0.516***
SE	(0.042)	(0.108)	(0.115)
p-value	[0.000]	[0.000]	[0.000]
TP+TPM	-0.282***	0.858***	-0.384***
SE	(0.039)	(0.145)	(0.098)
p-value	[0.000]	[0.000]	[0.001]
Individual FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Treated Mean	0.70	3.20	7.32
R^2	0.45	0.49	0.51
No. of Individuals	7,035	7,035	7,035
N	34,028	34,028	27,812

Notes: In this table, women are categorized by their employment status and education level in the pre-period, with employment defined as being employed in the last sampled period prior to the policy. The omitted group is the high-educated women who have bachelor's degrees or above. "Low-education" = Women who went to primary school or received no education. "Medium-education" = Women who went to middle school, secondary schools, or higher secondary schools. "Time for HH" = Time spent on household activities. "Travel Time" = Time spent on travel. "Time for Work" = Time spent on work done for the employer. All regressions include individual and quarter/wave fixed effects, as well as control for the average number of daily new confirmed cases as a share of the population. All units are hours per day. The treated mean is hours per day and is the average for employed married women in pre-periods and treated states. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

TABLE 6: Impact on Time Use Among Husbands Employed at Baseline

	(1) Husbands' % HH	(2) Travel Time	(3) Time for Work
Treat × Post (TP)	-0.020	-0.178**	-0.319
	(0.018)	(0.074)	(0.222)
Treat × Post × Low-education Wives (TPLW)	-0.023	-0.099	0.408*
	(0.019)	(0.086)	(0.230)
Treat × Post × Medium-education Wives (TPMW)	-0.042**	0.004	0.516**
	(0.020)	(0.086)	(0.231
TP+TPLW	-0.043***	-0.277***	0.090
SE	(0.009)	(0.064)	(0.061)
p-value	[0.000]	[0.000]	[0.160]
TP+TPMW	-0.062***	-0.174***	0.197**
SE	(0.010)	(0.058)	(0.087)
p-value	[0.000]	[0.008]	[0.035]
Individual FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Treated Mean	0.45	0.87	7.79
R^2	0.73	0.40	0.36
No. of Individuals	5,521	5,521	5,521
N	27,022	27,022	26,790

Notes: This table categorizes men based on their employment status in the last sampled pre-policy period, and restricts the sample to employed husbands of employed married women (the sample in Table 5). All regressions include individual and quarter/wave fixed effects, as well as the average number of daily new confirmed cases as a share of the population. The omitted group is the employed husbands whose wives have bachelor's degrees or above. "Husbands' % HH" = The time husbands spend on household chores divided by the total time the couple spends on chores. "Travel Time" = Time spent on travel. "Time for Work" = Time spent on work done for the employer. The unit is hours per day in columns 2-3. The treated mean is the average for employed husbands in treated states during the pre-periods. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is $p<0.1$, ** is $p<0.05$, and *** is $p<0.01$.

TABLE 7: Impact on Time Use Among Women Unemployed at Baseline

	(1) Travel Time	(2) Time for HH
Treat × Post	-0.028	-1.590***
	(0.063)	(0.257)
Individual FE	Yes	Yes
Wave FE	Yes	Yes
Treated Mean	0.19	5.46
R^2	0.54	0.73
No. of Individuals	6,643	6,643
N	31,987	31,987

Notes: We restrict the sample to women who are unemployed but actively seeking employment. We categorize women by their pre-period employment status. "Travel Time" = Time spent on travel. "Time for HH" = Time spent on household activities by unemployed women. All regressions include individual and quarter/wave fixed effects, as well as control for the average number of daily new confirmed cases as a share of the population. All units are hours per day. The treated mean is the average for unemployed women in pre-periods and treated states. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is $p<0.1$, ** is $p<0.05$, and *** is $p<0.01$.

TABLE 8: Impact on Household Food Expenditures Among Households with Married Women Employed at Baseline

	(1) All Educ. Levels	(2) Low Educ.	(3) Medium Educ.	(4) High Educ.
Panel A. Dependent Variable = Food Expenditure				
Treat × Post	-862.024***	-570.631***	-911.323***	-852.714***
	(153.224)	(141.477)	(190.826)	(121.930)
Treated Mean	5720.71	5208.77	5791.39	6774.62
R^2	0.77	0.76	0.74	0.84
Panel B. Dependent Variable = Food/Expenditure				
Treat × Post	0.001	0.007	0.003	-0.037***
	(0.009)	(0.012)	(0.009)	(0.006)
Treated Mean	0.50	0.52	0.51	0.43
R^2	0.67	0.67	0.64	0.79
HH FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
No. of HHs	7,522	2,769	3,926	791
N	49,126	17,348	26,208	5,264

Notes: We conduct the analysis on the sample of households that are also represented in the individual-level data. The dependent variable is the monthly household expenditure on all food items ("Food") in Panel A and is the monthly household expenditure on food as a share of total monthly household expenditure ("Food/Expenditure") in Panel B. Column 1 include **households with employed married women**; column 2 include **those with low-education employed married women**; column 3 include **households with medium-education employed married women**; and column 4 includes **those with high-educated employed married women**. All regressions include household and month fixed effects and control for the average number of daily new confirmed cases as a share of the population. The unit of outcome variables is Indian Rupees in Panel A. The treated mean is the average for households in treated states and pre-periods. The number of households reported in columns 2–4 does not necessarily add up to the number of households in column 1, as a household may include multiple employed married women with different education levels. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

TABLE 9: Travel Purpose and Distance: New vs. Continuous Users

	(1)	(2)	(3)	(4)
			Travel Purpose: Work	
	Travel for Work		Travel Distance (Bus) > 10 km	
New users	0.068*	0.066*	0.182***	0.198***
	(0.040)	(0.039)	(0.054)	(0.057)
Other Controls	No	Yes	No	Yes
Control Mean	0.44	0.44	0.52	0.52
R^2	0.00	0.07	0.02	0.06
N	1,106	1,106	496	496

Notes: We conduct regression analysis on the matched sample. In columns 1-2, we include all new users and continuous users; in columns 3-4, we restrict the sample to users whose travel purpose is work, which includes both work and job search, in the post-program period. "Travel for work" means the users' main travel purpose is work. "Travel Distance (Bus) > 10 km" is a dummy variable which equal to one if a user's average travel distance by buses after the introduction of the free bus program is over 10 kilometers and zero otherwise. Other controls include an individual's marital status and education level. Standard errors are clustered at the user level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

ONLINE APPENDIX

Gender-Specific Transportation Costs and Female Time Use: Evidence from India's *Pink Slip* Program

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A Weight Construction & DID

A.1 Construction of a Homogeneous Region Panel for SDID

In this paper, we employ the synthetic difference-in-differences approach (SDID) proposed by Arkhangelsky et al. (2021). The SDID method re-weights the outcome variable of the control units to align their time trends with those of the treated units and subsequently applies a DID analysis to the re-weighted panel. That is, this method constructs a synthetic counterfactual for the outcome variable to estimate causal effects. It should be noted that the SDID method focuses on aligning treated and control units based on pre-policy trends, rather than matching on both pre-treatment trends and levels. This makes it particularly effective in settings where level differences may exist, but pre-trends can be made comparable.

We apply the SDID method to panel data aggregated at the homogeneous region (HR) level, accounting for individual and household sampling weights in the aggregation process. There are two key reasons for this aggregation: (1) The HR level is the lowest unit at which the CPHS data is representative, and (2) aggregating household- and individual-level data at the HR level allows for better trend matching compared to state-level aggregation, which is broader and may obscure important regional variations. As discussed in Section 3.1, our analysis includes 96 HRs across 22 states. When matching the trends of the outcome variables, we also control for a set of covariates described below. All control variables, except for an individual's age, are categorical. Some categorical variables, such as religion, caste, and discipline, include "not stated" or "not applicable" observations. However, since these cases constitute a small fraction of the data, we classify them as a separate category rather than excluding them.[1]

[1]For example, less than 0.1% of observations fall under the "Not Stated" category for religion, while for caste, this proportion is 1.4%. In the case of discipline, approximately 70.9% of observations are classified as "Not Applicable." However, 99.9% of these cases correspond to individuals with an education level below higher secondary education, where selecting a discipline is not required. These cases would be captured by the education level variable.

We use six variables for the household-level data. The variable "size group of household" is a categorical variable that includes groups such as one member, three members, eight to ten members, and more than 15 members. It is based on the number of members in a household. The variable "age group of household" is a categorical variable that includes groups such as households dominated by children, households dominated by grown-ups, and balanced households with seniors. The variable "occupation group of household" is a categorical variable that includes groups such as wage laborers, self-employed professionals, entrepreneurs, and farmers. The occupation group of a household is based on the distribution of members of a household by the nature of their occupation. The CMIE classifies households into different groups based on certain rules and not just based on the occupation of the head of the household. The variable "education group of household" is a categorical variable that includes groups such as all graduates, graduates majority, and some literates. The education group of a household is based on the distribution of members of a household by their education level. The variable "gender" is a categorical variable that includes groups such as only males, only females, female majority, and balanced. The last variable we use is the average of new confirmed daily cases as a share of the state population. For each categorical variable, we then generate corresponding dummy variables, and these dummy variables, after aggregating to the state level, can be interpreted as the share of households having a certain characteristic. For example, one of the dummy variables created from "gender" is the share of households only having male members.

We use seven variables for the individual-level data: age, religion (e.g., Hindu and Muslim), caste (e.g., upper caste, scheduled castes, and scheduled tribes), discipline (e.g., law and medicine), marital status (e.g., married, unmarried, and divorced), literacy, and education level (e.g., primary school and middle school). Except for age, all other variables are categorical variables. Similarly, we generate the corresponding dummy variables before aggregating them to the state level. Again, we also include the average new confirmed daily cases as a share of the state population as one of our control variables.

Using this approach, we compare the outcomes of HRs in treated states with that of a weighted combination of HRs in control states. This weighted combination forms the "synthetic" treated states—regions without the free bus ride program but exhibiting similar pre-treatment trends as the treated group. In Table A1 and Table A2, we report the total weight assigned to each state, calculated by summing the SDID-estimated unit weights at the HR level within each state. Table A1 displays the state weights for household transportation expenditure variables. In Table A2, columns 1–3 show the state weights for the three time-use outcome variables for employed women, while columns 4–6 present the corresponding weights for employed married women. In both tables, we observe that Uttar Pradesh consistently receives one of the highest weights, whereas Chhattisgarh and Uttarakhand receive the lowest. We also report the time weights in Table A3 and Table A4 and find that the last pre-policy period receives the highest weight for most outcome variables.

With the estimated object (i.e., HR) and time weights from the SDID, we then integrate them with individual and household sampling weights. The final weights applied in our regression analyses (i.e., DID) for household- and individual-level data are defined as follows:

$$\text{Household-Level:} \qquad \text{Weight}_{ijt} = \text{HR Weight}_j \times \text{Time Weight}_t \times \text{HH Weight}_{it}, \quad \text{(A.1)}$$

$$\text{Individual-Level:} \qquad \text{Weight}_{ijt} = \text{HR Weight}_j \times \text{Time Weight}_t \times \text{Ind. Weight}_{it}. \quad \text{(A.2)}$$

In equations (A.1) and (A.2), "HR Weight$_j$" and "Time Weight$_t$" are the HR unit weights and time weights derived from the SDID, respectively. "HH Weight$_{it}$" refers to the sampling weight of a household in the CPHS data, while "Ind. Weight$_{it}$" corresponds to the sampling weight of an individual within a sampled household in the CPHS data.

TABLE A1: Aggregated State Weights: Household Transportation Expenditure

State	(1) BTF	(2) Transport	(3) BTF/Transport	(4) BTF/Expenditure
Andhra Pradesh	0.055	0.092	0.047	0.050
Bihar	0.072	0.034	0.054	0.068
Chandigarh	0.010	0.004	0.012	0.010
Chhattisgarh	0.036	0.060	0.032	0.043
Goa	0.011	0.008	0.014	0.010
Gujarat	0.039	0.054	0.052	0.051
Haryana	0.040	0.027	0.038	0.038
Himachal Pradesh	0.018	0.025	0.008	0.014
Jammu & Kashmir	0.028	0.023	0.024	0.021
Jharkhand	0.047	0.020	0.033	0.042
Karnataka	0.075	0.094	0.065	0.055
Kerala	0.045	0.064	0.036	0.041
Madhya Pradesh	0.066	0.040	0.075	0.066
Maharashtra	0.102	0.171	0.125	0.112
Odisha	0.043	0.063	0.047	0.042
Rajasthan	0.064	0.038	0.065	0.065
Telangana	0.034	0.068	0.035	0.028
Uttar Pradesh	0.157	0.077	0.156	0.156
Uttarakhand	0.008	0.007	0.011	0.011
West Bengal	0.048	0.030	0.071	0.077

Notes: This table reports the total weight assigned to each state, calculated by summing the SDID-estimated unit weights at the homogeneous region (HR) level within each state. These weights reflect the contribution of each state in constructing the synthetic control for the treated units. A reported weight of 0.000 indicates that the total is less than 0.0005, not that the weight is exactly zero.

Table A2: Aggregated State Weights: Time Use

	(1)	(2)	(3)	(4)	(5)	(6)
	Employed Women			Employed Married Women		
State	Travel Time	Time for HH	Time for Work	Travel Time	Time for HH	Time for Work
Andhra Pradesh	0.039	0.037	0.039	0.046	0.030	0.047
Bihar	0.080	0.083	0.068	0.096	0.090	0.070
Chandigarh	0.013	0.013	0.010	0.049	0.031	0.012
Chhattisgarh	0.025	0.014	0.040	0.035	0.017	0.027
Goa	0.014	0.001	0.009	0.008	0.001	0.000
Gujarat	0.047	0.032	0.054	0.045	0.022	0.059
Haryana	0.034	0.017	0.029	0.034	0.020	0.040
Himachal Pradesh	0.015	0.010	0.009	0.010	0.010	0.012
Jammu & Kashmir	0.001	0.025	0.014	0.003	0.018	0.013
Jharkhand	0.039	0.041	0.034	0.024	0.008	0.028
Karnataka	0.097	0.060	0.061	0.085	0.067	0.052
Kerala	0.040	0.050	0.035	0.024	0.044	0.034
Madhya Pradesh	0.057	0.092	0.073	0.033	0.072	0.058
Maharashtra	0.132	0.053	0.109	0.127	0.038	0.110
Odisha	0.079	0.054	0.047	0.068	0.043	0.049
Rajasthan	0.083	0.068	0.057	0.088	0.134	0.042
Telangana	0.018	0.016	0.033	0.008	0.009	0.039
Uttar Pradesh	0.108	0.218	0.198	0.145	0.227	0.200
Uttarakhand	0.001	0.012	0.011	0.007	0.020	0.014
West Bengal	0.079	0.105	0.070	0.065	0.100	0.094

Notes: This table reports the total weight assigned to each state, calculated by summing the SDID-estimated unit weights at the homogeneous region (HR) level within each state. These weights reflect the contribution of each state in constructing the synthetic control for the treated units. A reported weight of 0.000 indicates that the total is less than 0.0005, not that the weight is exactly zero.

Table A3: Time Weights: Household Transportation Expenditure

	(1)	(2)	(3)	(4)
$Time_t$	BTF	Transport	BTF/Transport	BTF/Expenditure
-4	0.204	0.195	0.000	0.064
-3	0.221	0.050	0.125	0.345
-2	0.000	0.000	0.059	0.000
-1	0.000	0.000	0.001	0.000
0	0.575	0.755	0.815	0.591

Notes: This table reports the estimated weights for each pre-treatment period and each outcome variable. A reported weight of 0.000 indicates that the weight is less than 0.0005, not that the weight is exactly zero.

Table A4: Time Weights: Time Use

	(1)	(2)	(3)	(4)	(5)	(6)
	Employed Women			Employed Married Women		
$Time_t$	Travel Time	Time for HH	Time for Work	Travel Time	Time for HH	Time for Work
-2	0.267	0.216	0.186	0.314	0.137	0.102
-1	0.377	0.157	0.328	0.505	0.268	0.447
0	0.356	0.627	0.486	0.180	0.596	0.451

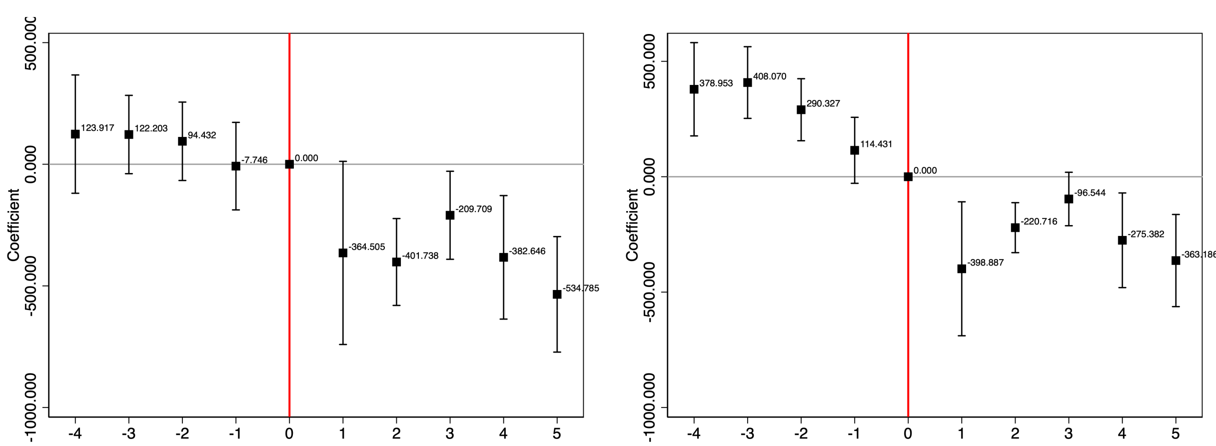
Notes: This table reports the estimated weights for each pre-treatment period and each outcome variable. A reported weight of 0.000 indicates that the weight is less than 0.0005, not that the weight is exactly zero.

A.2 Comparison with the Standard DID

States that have implemented the *Pink Slip* program may differ from other states, including neighboring ones, in various ways, raising concerns about potential pre-trends that could bias standard DID estimates. To address this concern, we thus employ the DID method with SDID weights, which adjust discrepancies in pre-treatment trends. We present two examples to demonstrate the importance of incorporating SDID weights. In Figure A1, we plot the event study graphs of household monthly expenditure on all food items, and in Figure A2, we plot the event study graphs of travel time among employed women. In Figure A1a and Figure A2a, we incorporate the HR and time weights into the DID, whereas in Figure A1b and Figure A2b, we do not. As clearly illustrated, without integrating SDID weights into our DID specification, the parallel trends assumption would not hold.

Furthermore, in Table A5, we report the results on household expenditures with and without SDID weights. All of the estimated coefficients with SDID weights in Panel A, which serve as our baseline results, are smaller in absolute terms than those obtained without HR and time weighting in Panel B. This suggests that omitting SDID weights could lead to an overestimation of the program's effects due to the presence of pre-trends.

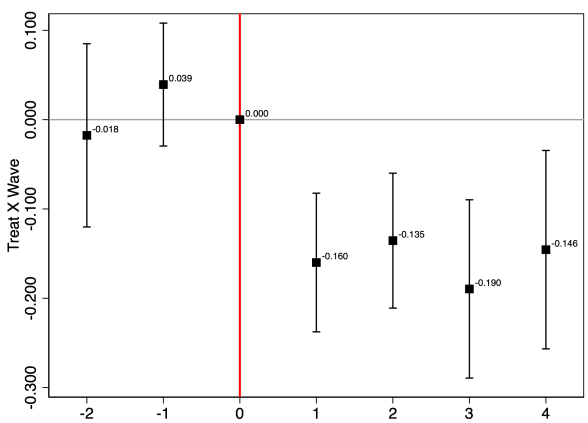
FIGURE A1: Event Study Graphs: Monthly Household Expenditure on Food



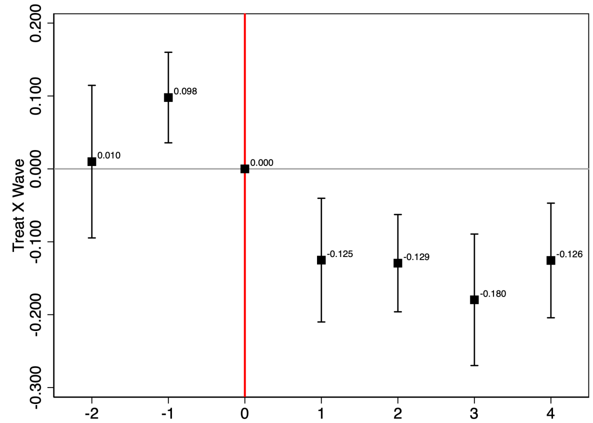
(a) Food (With SDID Weights) (b) Food ((Without SDID Weights)

Notes: "Food" = Total monthly household expenditure on all food items. We analyze the sample of households that are also presented in the PoI data. The time unit of analysis is monthly, and $t = 0$ is one month before the program starts. The program started in April and May 2021 in Punjab and Tamil Nadu, respectively. The period of analysis is November 2020-August 2021 for Punjab and December 2020-September 2021 for Tamil Nadu. In Figure A1a, we apply the object (i.e., homogeneous region) and time weights from the synthetic difference-in-differences method. But, in Figure A1b, we include only household sampling weights and do not incorporate the SDID weights in the regression. All regressions include household and month fixed effects and control for the average number of daily new confirmed cases as a share of the population. Standard errors are clustered at the state level. Confidence intervals are at the 95 percent level.

FIGURE A2: Event Study Graphs: Travel Time for Women Employed at Baseline



(a) Travel Time (With SDID Weights)



(b) Travel Time (Without SDID Weights)

Notes: We restrict the sample to women who were employed in the last sampled period before the policy. In Figure A2a, we apply the object (i.e., homogeneous region) and time weights from the synthetic difference-in-differences method. But, in Figure A2b, we include only individual sampling weights and do not incorporate the SDID weights in the regression. Here, $t = 0$ represents one wave (four months) before the program. The program started in April and May 2021 in Punjab and Tamil Nadu, respectively. The time period of analysis here is May-August 2020 to May-August 2022 for both Punjab and Tamil Nadu. All regressions include individual and quarter/wave fixed effects, as well as control for the average number of daily new confirmed cases as a share of the population. All units are hours per day. Standard errors are clustered at the state level. Confidence intervals are at the 95 percent level.

TABLE A5: Impact on Household Transportation Expenditures (With and Without SDID Weights)

	(1) BTF	(2) Transport	(3) BTF/Transport	(4) BTF/Expenditure
Panel A. Baseline (With SDID Weights)				
Treat × Post	-25.882**	-48.507***	-0.060***	-0.002**
	(10.337)	(12.898)	(0.013)	(0.001)
R^2	0.71	0.23	0.72	0.73
Panel B. Without SDID Weights				
Treat × Post	-38.237***	-76.439***	-0.075***	-0.003***
	(8.248)	(8.655)	(0.013)	(0.001)
R^2	0.74	0.42	0.75	0.74
HH FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Treated Mean	128.17	398.45	0.35	0.01
No. of HHs	115,745	115,745	115,745	115,745
N	785,868	785,868	785,868	785,868

Notes: "Expenditure" = Total monthly household expenditure. "Transport" = Total monthly household expenditure on transport. "BTF" = Monthly household expenditure on daily bus/train/ferry fare. We analyze the sample of households that are also represented in the individual-level data. All regressions include household and wave fixed effects, as well as control for the average number of daily new confirmed cases as a share of the population. In panel B, we do not incorporate the weights derived from the SDID. The treated mean is the average expenditures for households in treated states during pre-periods. Standard errors are clustered at the state level. * is $p<0.1$, ** is $p<0.05$, and *** is $p<0.01$.

A.3 Staggered SDID

Since the *Pink Slip* program was implemented in different months (April 1, 2021, in Punjab and May 7, 2021, in Tamil Nadu), one might be concerned about whether the results hold when accounting for the staggered rollout. In the People of India (PoI) data, surveys are conducted in four-month waves: January–April, May–August, and September–December. As discussed in Section 3.1, we classify the waves from May–August 2021 to May–August 2022 as the post-periods, and the waves from May–August 2020 to January–April 2021 as the pre-periods for both treated states. Therefore, staggered adoption is not a concern for our time-use analysis.

In the Consumption Pyramids (CP) data section, the survey is conducted monthly. We define rounds after April 2021 as the post-period for Punjab and rounds after May 2021 as the post-period for Tamil Nadu. In the main analysis, we include data from five months before and five months after the program implementation. To account for the staggered treatment timing, we apply the staggered adoption design of the SDID method proposed by Clarke et al. (2024) to the aggregated HR-level data. The study period is from November 2020 to September 2021 for all homogeneous regions in the 22 states and union territories. We report the results with three different inference methods in Table A6. As shown, the estimated coefficients are similar in magnitude to our main findings in Table 2, and if anything, slightly larger—reinforcing the robustness of our results on transportation expenditure.

TABLE A6: Impact on Household Transportation Expenditures: HR-Level Data with Staggered SDID and Different Inference Methods

	(1) BTF	(2) Transport	(3) BTF/Transport	(4) BTF/Expenditure
Treat × Post	-32.473	-66.384	-0.105	-0.002
Bootstrap SE	(15.349)**	(26.285)**	(0.033)***	(0.001)**
Jackknife SE	(16.439)**	(32.004)**	(0.033)***	(0.001)*
Placebo SE	(13.753)**	(19.248)***	(0.045)**	(0.001)*
No. of HRs	96	96	96	96
No. of Time Periods	11	11	11	11

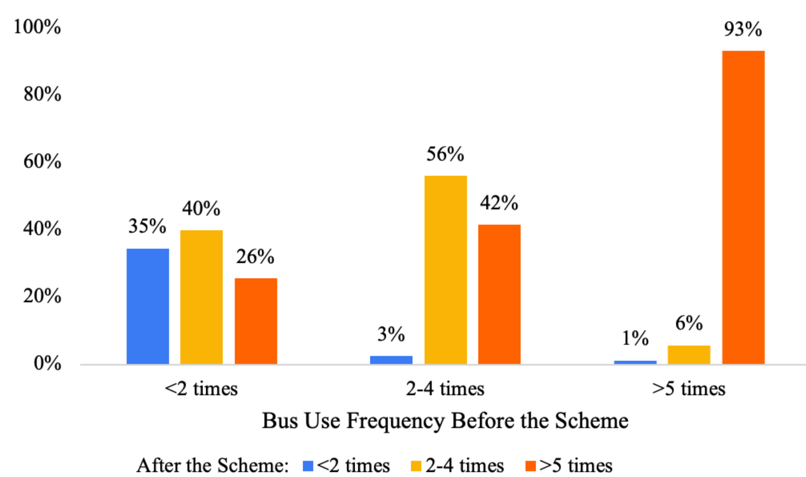
Notes: This table replicates Table 2 in the main text. However, here we aggregate household-level data to the homogeneous region level and then apply the staggered synthetic difference-in-differences method (Clarke et al., 2024) to the homogeneous-region panel data. In total, we have 96 homogeneous regions in 22 Indian states. "BTF" = Monthly household expenditure on daily bus/train/ferry fare. "Transport" = Total monthly household expenditure on transport. "Expenditure" = Total monthly household expenditure. Standard errors are reported using three inference procedures: bootstrap, jackknife, and placebo. Statistical significance is indicated as follows: * is $p<0.1$, ** is $p<0.05$, and *** is $p<0.01$.

B CAG Survey on Women's Bus Fare Sensitivity

The CPHS data lack individual-level information on the number of trips, distance traveled, or the monetary and time cost of trips, limiting our ability to assess women's sensitivity to bus fare changes. To address this gap, we draw on evidence from the CAG survey, which included three relevant questions: "Before the free bus program, how often did you take an ordinary government or private bus?", "After the free bus program, how often do you take the free bus?", and "How much did you spend on bus tickets per day before the free bus program?"

For the first two questions, responses were recorded using categorical frequency options: (1) less than 2 times per week (assigned a value of 1), (2) 2 to 4 times per week (assigned a value of 3), and (3) 5 or more times per week (assigned a value of 6, providing a lower bound). The third question on daily expenditure was also a multiple-choice question, with the following categories: (1) less than ₹10 (assigned a value of 5), (2) ₹11–30 (assigned 20), (3) ₹31–50 (assigned 40), (4) ₹51–70 (assigned 60), and (5) more than ₹71 (assigned 80). We use these assigned values as proxies for bus usage frequency and pre-program spending to examine the relationship between baseline travel costs and changes in usage.

FIGURE B1: Weekly Bus Use Frequency Before and After the Program



Notes: The survey data is from the Citizen Consumer and Civic Action Group (Narayanan, 2024). In this figure, we show the distribution of weekly bus use frequency among female bus users aged 18–50 who did not receive any type of bus fare concession prior to the program, both before and after its implementation. The percentages should be interpreted as follows: for example, the first blue bar on the left indicates that 35% of women who took the bus fewer than two times per week before the program continued to do so after its implementation.

We first show that ridership increased after the policy shift. In Figure B1, we display the distribution of bus use frequency among female bus users aged 18–50 who did not receive any bus fare concession before the program. The x-axis shows the frequency of bus usage before the policy change in three bins/categories (less than 2 times, between 2-4 times a week, and more than 5 times a week). The y-axis shows the share of women in these categories after the policy change. Among those who used buses fewer than two times per week before the program, 26% shifted to using buses more than five times per week afterward. Similarly, among those who previously used buses 2–4 times per week, 42% increased their usage to over five times per week.

Next, we regress the change in trip frequency on daily expenditure on bus tickets before the policy (noting that the post-policy price is zero). The estimated coefficient is –0.015 ($p < 0.01$), indicating that a one standard deviation decrease in daily bus expenditure is associated with a 0.14 standard deviation increase in weekly bus trips.[2] This confirms that as the price falls, ridership increases.

[2] The standard deviation of the price before the policy is 15.63, and the standard deviation of the change in trip frequency is 1.59. The standardized effect is calculated as $-0.015 \times 15.63/1.59 = -0.14$.

C Cost-Benefit Analysis

We conduct a back-of-the-envelope cost-benefit analysis based on our estimated treatment effects to shed light on whether the benefits of the *Pink Slip* program outweigh its fiscal costs.

Cost On the cost side, we focus on the two treated states included in our main analysis: Tamil Nadu and Punjab. In Tamil Nadu, the state government reimburses ₹16 for each free bus ride taken by women.[3] As of December 2024, the program had supported approximately 5.95 billion free rides.[4] This corresponds to approximately 1.6 billion rides annually. Multiplying this by the reimbursement rate yields an estimated annual program cost of ₹26 billion. In Punjab, the ridership under the program is about 142.9 mn from March 2022 to March 2023.[5] Although the Punjab government does not report a fixed reimbursement per ride, we assume the same per-ride cost of ₹16 for comparability, yielding an estimated annual cost of ₹2.3 billion. Adding this to the estimated cost in Tamil Nadu, the total direct annual expenditure for the two states amounts to approximately ₹28.3 billion. To account for administrative and implementation expenses, we conservatively assume an additional 10% of direct costs, which adds ₹2.8 billion and brings the total estimated annual program cost to ₹31.1 billion.

Benefits On the benefit side, women and their households gain from changes in labor supply among employed unmarried and married women, shifts in the labor supply of spouses of employed married women, and savings in expenditures such as food. At the same time, married employed women with low and medium education reduce their labor supply. We account for all these components in computing the total benefit. All the foregone wage estimates below assume an 8-hour workday and 20 workdays per month.

- Labor supply of employed unmarried women: We estimate that employed unmarried women increased their daily working time by 26 minutes (column 3 of Panel A in Table 4) following the program's implementation. The average pre-program monthly wage for this group in treated states was ₹12,599, which corresponds to approximately ₹34 for 26 minutes of work, based on the InP data. According to the 2011 Census, there are approximately 5.3 mn unmarried women aged 15 to 55 in

[3]The statistic is from this website.
[4]The statistic is from this news article.
[5]The statistic is from this website.

Tamil Nadu and Punjab.[6] Given a labor force participation rate of 25.5% and an unemployment rate of 5.8%, we estimate about 1.3 mn unmarried women are employed (calculated as 5.3 mn $\times$ 25.5% $\times$ $(1 - 5.8\%)$). Assuming all of these women use free buses and work 240 days per year,[7] this implies a total annual wage gain of approximately ₹10.4 billion.

- Labor supply of employed married women: We find that employed married women reduced their labor supply, with low-education women working 31 minutes less and medium-education women 23 minutes less per day. Based on the 2011 Census, in Punjab (Tamil Nadu), 13.9% (11.7%) of women aged 15 to 59 had attended an educational institution, and among those, 73.7% (80.1%) are classified as medium-education.[8] We define women who have never attended school or completed at most primary education as low-education; 87.6% (88.9%) of women fall into this category in Punjab (Tamil Nadu). Using these proportions, we estimate that there are approximately 1.2 mn (1.7 mn) low-education employed married women and 139,679 (180,775) medium-education employed married women in Punjab (Tamil Nadu). The average pre-program monthly wage for low-education employed married women in treated states was ₹4,340 (equivalent to ₹14.0 per 31 minutes of work), and for medium-education employed married women it was ₹7,399 (₹17.8 per 23 minutes), based on CPHS data. Assuming all of these women used free buses and worked 240 days per year, this implies a total annual wage loss of approximately ₹11.1 billion.

  Meanwhile, employed husbands of medium-education employed married women increased their labor supply by 12 minutes per day (column 4 of Panel B in Table 6). We account for this gain as well. The average pre-program monthly wage for this group in treated states was ₹10,992, which corresponds to approximately ₹13.6 per 12 minutes of work. This implies a total annual gain of approximately ₹1.05 billion.

- Food Expenditure: We find that households with women, regardless of employment status, in treated states save approximately ₹504 per month on food expenditure (column 1 of Panel A in Table F14). We interpret this reduction as a reflection of cost

[6] The marriage rate among women aged 15 to 55 is 71.1% in Punjab and 72.9% in Tamil Nadu, based on the 2011 Census.

[7] The CPHS data does not contain information on whether an individual actually used buses. Our estimate of a 26-minute increase is therefore an average across all employed unmarried women, regardless of bus usage status. We also assume a five-day work week and do not account for holidays. However, it should be noted that the standard work week in India typically runs from Monday to Saturday, i.e., six days. Therefore, 240 annual workdays is a conservative, lower-bound estimate.

[8] We use the 15–59 age range here because the 2011 Census table we used for this specific calculation does not provide a separate breakdown for women aged up to 55.

savings rather than decreased consumption. This is supported by the CAG survey, where 42% of women reported using the money saved from the free bus program to buy food. Despite this reported shift toward food spending, total food expenditure still declined, suggesting that households are buying similar—or possibly greater—quantities at lower cost. These savings likely result from improved access to more affordable stores or the elimination of distance-based price markups, as the *Pink Slip* program enables women to travel farther to shop or buy in bulk at better prices.

According to the 2011 Census, the total number of households is 5,513,071 in Punjab and 18,524,982 in Tamil Nadu. In the CPHS data, about 85.7% of households include at least one woman aged between 15 and 55. Based on this, the estimated total annual savings on food expenditure amount to approximately ₹124.5 billion—calculated as $(5,513,071 + 18,524,982) \times 85.6\% \times 504 \times 12$.

Comparing Benefits to Costs This analysis highlights significant variations in benefits. Not everyone benefits in the labor market. Net increase in labor supply leads to gains of approximately ₹0.35 billion annually. However, the total program cost is ₹31.1 billion. Thus, if we only compare labor market outcomes benefits to costs, we would conclude that the program is not cost-effective. However, once we include savings in food expenditure, the program yields an estimated net benefit of approximately ₹94 billion annually, which might be a conservative lower bound (Note that these savings would outweigh costs even if the overhead cost was 100% of the direct cost instead of the 10% assumed). The detailed calculations are presented in Appendix Table C1. While our analysis focuses on three primary benefits, there are additional benefits that we are unable to monetize, such as improved safety perceptions, increased autonomy from enhanced mobility, and greater household production of unpaid work. Thus, the program's overall impact is likely larger. The *Pink Slip* program, especially when accounting for household savings in food expenditure, generates substantial net gains.

TABLE C1: Cost-Benefit Analysis

Item	Amonut
Reimbursement from the government	-28.3 billion
Indirect cost (10% of direct cost)	- 2.8 billion
Total Cost	-31.1 billion
Increased labor supply from employed unmarried women	+10.4 billion
Decreased labor supply from employed married women	-11.1 billion
Increased labor supply from employed husbands of medium-educated employed wives	+ 1.05 billion
Saving on food expenditure	+ 124.5 billion
Total Benefit	+ 124.85 billion
Net Benefit	+93.8 billion

Notes: All amounts are in Indian rupees.

D Robustness Checks

D.1 SE at the Homogeneous Region Level

TABLE D1: Impact on Household Transportation Expenditures (Clustered SE at the Homogeneous Region Level)

	(1) BTF	(2) Transport	(3) BTF/Transport	(4) BTF/Expenditure
Treat × Post	-25.882**	-48.507**	-0.060***	-0.002**
	(12.069)	(22.511)	(0.019)	(0.001)
HH FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Treated Mean	128.17	398.45	0.35	0.01
R^2	0.71	0.23	0.72	0.73
No. of HHs	115,745	115,745	115,745	115,745
N	785,868	785,868	785,868	785,868

Notes: We conduct analysis on the sample of households that are also represented in the individual data. "Transport" = Total monthly household expenditure on transport. "BTF" = Monthly household expenditure on daily bus/train/ferry fare. "Expenditure" = Total monthly household expenditure. All regressions include household and month fixed effects and control for the average number of daily new confirmed cases as a share of the population. The unit of outcome variables in columns 1-2 is Indian Rupees. The treated mean is the average for households in treated states and pre-periods. Standard errors are clustered at the homogeneous region level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

TABLE D2: Impact on Time Use Among **Married Women Employed at Baseline** (Clustered SE at the Homogeneous Region Level)

	(1) Travel Time	(2) Time for HH	(3) Time for Work
Treat × Post	-0.314***	0.729***	-0.385***
	(0.067)	(0.230)	(0.145)
Individual FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Treated Mean	0.70	3.20	7.32
R^2	0.45	0.49	0.51
No. of Individuals	7,035	7,035	7,035
N	34,028	34,028	27,812

Notes: In this table, we categorize women based on their employment status in the last sampled pre-policy period. "Travel Time" = Time spent on travel. "Time for HH" = Time spent on household activities. "Time for Work" = Time spent on work done for the employer. All regressions include individual and quarter/wave fixed effects, as well as control for the average number of daily new confirmed cases as a share of the population. All units are hours per day. The treated mean is hours per day and is the average for employed women in treated states during pre-periods. Standard errors are clustered at the homogeneous region level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

TABLE D3: Impact on Time Use Among **Married Women Employed at Baseline**, by Education (Clustered SE at the Homogeneous Region Level)

	(1) Travel Time	(2) Time for HH	(3) Time for Work
Treat × Post (TP)	-0.175*	0.094	-0.049
	(0.104)	(0.188)	(0.294)
Treat × Post × Low-education (TPL)	-0.225**	0.663***	-0.467*
	(0.111)	(0.186)	(0.245)
Treat × Post × Medium-education (TPM)	-0.107	0.764**	-0.335
	(0.111)	(0.293)	(0.411)
TP+TPL	-0.399***	0.756***	-0.516***
SE	(0.054)	(0.163)	(0.150)
p-value	[0.000]	[0.000]	[0.001]
TP+TPM	-0.282***	0.858**	-0.384
SE	(0.067)	(0.345)	(0.240)
p-value	[0.000]	[0.015]	[0.113]
Individual FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Treated Mean	0.70	3.20	7.32
R^2	0.45	0.49	0.51
No. of Individuals	7,035	7,035	7,035
N	34,028	34,028	27,812

Notes: In this table, women are categorized by their employment status and education level in the pre-period, with employment defined as being employed in the last sampled period prior to the policy. The omitted group is the highly educated women who have bachelor's degrees or above. "Low-education" = Women who went to primary schools or received no education. "Medium-education" = Women who went to middle school, secondary schools, or higher secondary schools. "Time for HH" = Time spent on household activities. "Travel Time" = Time spent on travel. "Time for Work" = Time spent on work done for the employer. All regressions include individual and quarter/wave fixed effects, as well as control for the average number of daily new confirmed cases as a share of the population. All units are hours per day. The treated mean is hours per day and is the average for employed married women in treated states and pre-periods. Standard errors are clustered at the homogeneous region level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

D.2 Jackknife-Based Inference

TABLE D4: Jackknife-Based Inference: Household Expenditures

Variable	(1) Estimated Coefficient	(2) SE (Baseline)	(3) p-value (Baseline)	(4) $\sqrt{\hat{V}^{jack}}$	(5) p-value (Jackknife)
BTF	TP: -25.882	10.337	0.02	13.714	0.06
Transport	TP: -48.507	12.898	0.00	25.894	0.06
BTF/Transport	TP: -0.060	0.013	0.00	0.023	0.01
BTF/Expenditure	TP: -0.002	0.001	0.00	0.001	0.07

Notes: We conduct analysis on the sample of households that are also represented in the individual data. The total number of households included in the sample is 115,745. "BTF" = Monthly household expenditure on daily bus/train/ferry fare. "Transport" = Total monthly household expenditure on transport. "Expenditure" = Total monthly household expenditure. "Food" = Total monthly household expenditure on food. For the jackknife-based inference, we drop observations from one homogeneous region at a time. In column 1, we report the estimated coefficients from the main results. Columns 2 and 3 present the corresponding standard errors clustered at the state level and their associated p-values. Column 4 reports the square root of the jackknife variance, calculated using the formula proposed in (Arkhangelsky et al., 2021), and column 5 displays the corresponding p-values.

TABLE D5: Jackknife-Based Inference: Time Use Among Married Women Employed at Baseline

Variable	(1) Estimated Coefficient	(2) SE (Baseline)	(3) p-value (Baseline)	(4) $\sqrt{\hat{V}^{jack}}$	(5) p-value (Jackknife)
Panel A. Time Use for Employed Married Women (Panel B of Table 4)					
Travel Time	TP: -0.314	0.048	0.00	0.105	0.00
Time for HH	TP: 0.729	0.141	0.00	0.277	0.01
Time for Work	TP: -0.385	0.133	0.01	0.186	0.04
Panel B. Time Use for Employed Married Women by Education (Table 5)					
Travel Time	TP: -0.175	0.065	0.01	0.125	0.16
	TP+TPL: -0.399	0.042	0.00	0.145	0.01
	TP+TPM: -0.282	0.039	0.00	0.084	0.00
Time for HH	TP: 0.094	0.159	0.16	0.212	0.66
	TP+TPL: 0.756	0.108	0.00	0.177	0.00
	TP+TPM: 0.858	0.145	0.00	0.481	0.07
Time for Work	TP: -0.049	0.319	0.88	0.327	0.88
	TP+TPL: -0.516	0.115	0.00	0.135	0.00
	TP+TPM: -0.384	0.098	0.00	0.262	0.14

Notes: In this table, women are categorized by their employment status and education level in the pre-period, with employment defined as being employed in the last sampled period prior to the policy. "Travel Time" = Time spent on travel. "Time for HH" = Time spent on household activities. "Time for Work" = Time spent on work done for the employer. "TP" = Treat × Post. "TP+TPL" = Treat × Post + Treat × Post × Low-education. "TP+TPM" = Treat × Post + Treat × Post × Medium-education. For the jackknife-based inference, we drop observations from one homogeneous region at a time. In column 1, we report the estimated coefficients from the main results. Columns 2 and 3 present the corresponding standard errors clustered at the state level and their associated p-values. Column 4 reports the square root of the jackknife variance, calculated using the formula proposed in (Arkhangelsky et al., 2021), and column 5 displays the corresponding p-values.

D.3 Age Restriction: 15 to 49

TABLE D6: Impact on Household Transportation Expenditures (Households Having Women Aged between 15 and 49)

	(1) BTF	(2) Transport	(3) BTF/Transport	(4) BTF/Expenditure
Treat × Post	-25.483**	-44.087***	-0.064***	-0.002**
	(10.676)	(13.082)	(0.013)	(0.001)
HH FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Treated Mean	126.94	395.60	0.34	0.01
R^2	0.71	0.22	0.72	0.73
No. of HHs	103,721	103,721	103,721	103,721
N	703,922	703,922	703,922	703,922

Notes: We conduct analysis on the sample of households who are also represented in the individual data and who have women aged between 15 and 49. "Transport" = Total monthly household expenditure on transport. "BTF" = Monthly household expenditure on daily bus/train/ferry fare. "Expenditure" = Total monthly household expenditure. All regressions include household and month fixed effects and control for the average number of daily new confirmed cases as a share of the population. The unit of outcome variables in columns 1-2 is Indian Rupees. The treated mean is the average for households in treated states and pre-periods. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

TABLE D7: Impact on Time Use for **Married Women Employed at Baseline** (Aged Between 15 and 49)

	(1) Travel Time	(2) Time for HH	(3) Time for Work
Treat × Post	-0.319***	0.769***	-0.438**
	(0.049)	(0.150)	(0.174)
Individual FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Treated Mean	0.72	3.23	7.25
R^2	0.44	0.50	0.51
No. of Individuals	6,088	6,088	6,088
N	29,429	29,429	24,098

Notes: We restrict the sample to employed married women aged between 15 and 49. In this table, women are categorized according to their employment status in the last sampled pre-policy period. "Travel Time" = Time spent on travel. "Time for HH" = Time spent on household activities. "Time for Work" = Time spent on work done for the employer. All regressions include individual and quarter/wave fixed effects, as well as control for the average number of daily new confirmed cases as a share of the population. All units are hours per day. The treated mean is hours per day and is the average for employed women in treated states during pre-periods. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

TABLE D8: Impact on Time Use Among **Married Women Employed at Baseline**, by Education (Aged Between 15 and 49)

	(1) Travel Time	(2) Time for HH	(3) Time for Work
Treat × Post (TP)	-0.192**	-0.020	0.029
	(0.070)	(0.181)	(0.376)
Treat × Post × Low-education (TPM)	-0.228***	0.830***	-0.656*
	(0.063)	(0.168)	(0.370)
Treat × Post × Medium-education (TPM)	-0.096	0.959***	-0.503
	(0.060)	(0.212)	(0.369)
TP+TPL	-0.421***	0.810***	-0.627***
SE	(0.042)	(0.112)	(0.124)
p-value	[0.000]	[0.000]	[0.000]
TP+TPM	-0.288***	0.939***	-0.474***
SE	(0.037)	(0.125)	(0.094)
p-value	[0.000]	[0.000]	[0.000]
Individual FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Treated Mean	0.72	3.23	7.25
R^2	0.45	0.50	0.51
No. of Individuals	6,088	6,088	6,088
N	29,429	29,429	24,098

Notes: We restrict the sample to employed married women aged between 15 and 49. In this table, we categorize women based on their employment status and education level during the pre-period, with employment defined as being employed in the last sampled period prior to the policy. The omitted group is the high-education women who have bachelor's degrees or above. "Low-education" = Women who went to primary schools or received no education. "Medium-education" = Women who went to middle school, secondary schools, or higher secondary schools. "Time for HH" = Time spent on household activities. "Travel Time" = Time spent on travel. "Time for Work" = Time spent on work done for the employer. All regressions include individual and quarter/wave fixed effects, as well as control for the average number of daily new confirmed cases as a share of the population. All units are hours per day. The treated mean is hours per day and is the average for employed married women in treated states during pre-periods. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

D.4 COVID-19 Policy Controls

TABLE D9: Impact on Household Transportation Expenditures (Robustness to Policy Controls)

	(1) BTF	(2) Transport	(3) BTF/Transport	(4) BTF/Expenditure
Treat × Post	-27.214**	-50.478***	-0.063***	-0.002**
	(10.085)	(13.136)	(0.015)	(0.001)
HH FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Treated Mean	128.17	398.45	0.35	0.01
R^2	0.71	0.23	0.72	0.73
No. of HHs	115,745	115,745	115,745	115,745
N	785,868	785,868	785,868	785,868

Notes: This table replicates Table 2 in the main text by adding the two following policy variables as controls: the share of days the state government had either recommended or required closing public transport in a month, and the share of days the state government had either recommended or required individuals not to leave the house in a month. "BTF" = Monthly household expenditure on daily bus/train/ferry fare. "Transport" = Total monthly household expenditure on transport. "Expenditure" = Total monthly household expenditure. We analyze the sample of households that are also represented in the individual data. All regressions include household and month fixed effects and control for the average number of daily new confirmed cases as a share of the population. The treated means in columns 1 and 2 are in Rupees. The treated mean is the average for households in treated states and pre-periods. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

TABLE D10: Impact on Time Use Among **Married Women Employed at Baseline** (Robustness to Policy Controls)

	(1) Travel Time	(2) Time for HH	(3) Time for Work
Treat × Post	-0.309***	0.730***	-0.385***
	(0.039)	(0.135)	(0.128)
Individual FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Treated Mean	0.70	3.20	7.32
R^2	0.45	0.49	0.51
No. of Individuals	7,035	7,035	7,035
N	34,028	34,028	27,812

Notes: In this table, we categorize women based on their employment status in the last sampled period prior to the policy. "Travel Time" = Time spent on travel. "Time for HH" = Time spent on household activities. "Time for Work" = Time spent on work done for the employer. All regressions include individual and quarter/wave fixed effects, as well as control for the average number of daily new confirmed cases as a share of the population. We also add the two following policy variables as controls: the share of days the state government had either recommended or required closing public transport in a month, and the share of days the state government had either recommended or required individuals not to leave the house in a month. All units are hours per day. The treated mean is hours per day and is the average for employed women in treated states during pre-periods. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

TABLE D11: Impact on Time Use Among **Married Women Employed at Baseline**, by Education (Robustness to Policy Controls)

	(1) Travel Time	(2) Time for HH	(3) Time for Work
Treat × Post (TP)	-0.194***	0.127	-0.048
	(0.052)	(0.170)	(0.331)
Treat × Post × Low-education (TPM)	-0.195***	0.624***	-0.466
	(0.049)	(0.139)	(0.336)
Treat × Post × Medium-education (TPM)	-0.082	0.727***	-0.338
	(0.049)	(0.196)	(0.332)
TP+TPL	-0.389***	0.751***	-0.514***
SE	(0.036)	(0.106)	(0.116)
p-value	[0.000]	[0.000]	[0.000]
TP+TPM	-0.276***	0.854***	-0.386***
SE	(0.034)	(0.140)	(0.095)
p-value	[0.000]	[0.000]	[0.001]
Individual FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Treated Mean	0.70	3.20	7.32
R^2	0.45	0.49	0.51
No. of Individuals	7,035	7,035	7,035
N	34,028	34,028	27,812

Notes: In this table, women are categorized by their employment status and education level in the pre-period, with employment defined as being employed in the last sampled period prior to the policy. The omitted group is the high-education women who have bachelor's degrees or above. "Low-education" = Women who went to primary schools or received no education. "Medium-education" = Women who went to middle school, secondary schools, or higher secondary schools. "Time for HH" = Time spent on household activities. "Travel Time" = Time spent on travel. "Time for Work" = Time spent on work done for the employer. All regressions include individual and quarter/wave fixed effects, as well as control for the average number of daily new confirmed cases as a share of the population. We also add the two following policy variables as controls: the share of days the state government had either recommended or required closing public transport in a month, and the share of days the state government had either recommended or required individuals not to leave the houses in a month. All units are hours per day. The treated mean is hours per day and is the average for employed married women in treated states during pre-periods. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is $p<0.1$, ** is $p<0.05$, and *** is $p<0.01$.

D.5 Excluding the Delta Wave

TABLE D12: Impact on Household Transportation Expenditures (Remove the Delta Wave)

	(1) BTF	(2) Transport	(3) BTF/Transport	(4) BTF/Expenditure
Treat × Post	-20.152**	-45.416***	-0.049***	-0.001**
	(8.266)	(12.924)	(0.009)	(0.001)
HH FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
Treated Mean	128.17	398.74	0.34	0.01
R^2	0.72	0.24	0.75	0.75
No. of HHs	114,936	114,936	114,936	114,936
N	639,375	639,375	639,375	639,375

Notes: This table replicates Table 2 in the main text by changing the post-policy periods. We exclude the first two post-periods. "Expenditure" = Total monthly household expenditure. "Transport" = Total monthly household expenditure on transport. "BTF" = Monthly household expenditure on daily bus/train/ferry fare. We analyze the sample of households that are also represented in the individual data. All regressions include household and month fixed effects and control for the average number of daily new confirmed cases as a share of the population. The unit of outcome variables in columns 1-2 is Indian Rupees. The treated mean is the average for households in treated states and pre-periods. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

TABLE D13: Impact on Time Use Among **Married Women Employed at Baseline** (Remove the Delta Wave)

	(1) Travel Time	(2) Time for HH	(3) Time for Work
Treat × Post	-0.291***	0.673***	-0.369***
	(0.044)	(0.129)	(0.114)
Individual FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Treated Mean	0.71	3.32	7.31
R^2	0.44	0.48	0.50
No. of Individuals	6,552	6,552	6,552
N	32,647	32,647	27,291

Notes: We restrict the sample to employed married women and drop the 23rd wave (May-August 2021). In this table, we categorize women based on their employment status in the last sampled period prior to the policy. "Travel Time" = Time spent on travel. "Time for HH" = Time spent on household activities. "Time for Work" = Time spent on work done for the employer. All regressions include individual and quarter/wave fixed effects, as well as control for the average number of daily new confirmed cases as a share of the population. All units are hours per day. The treated mean is hours per day and is the average for employed women in treated states during pre-periods. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

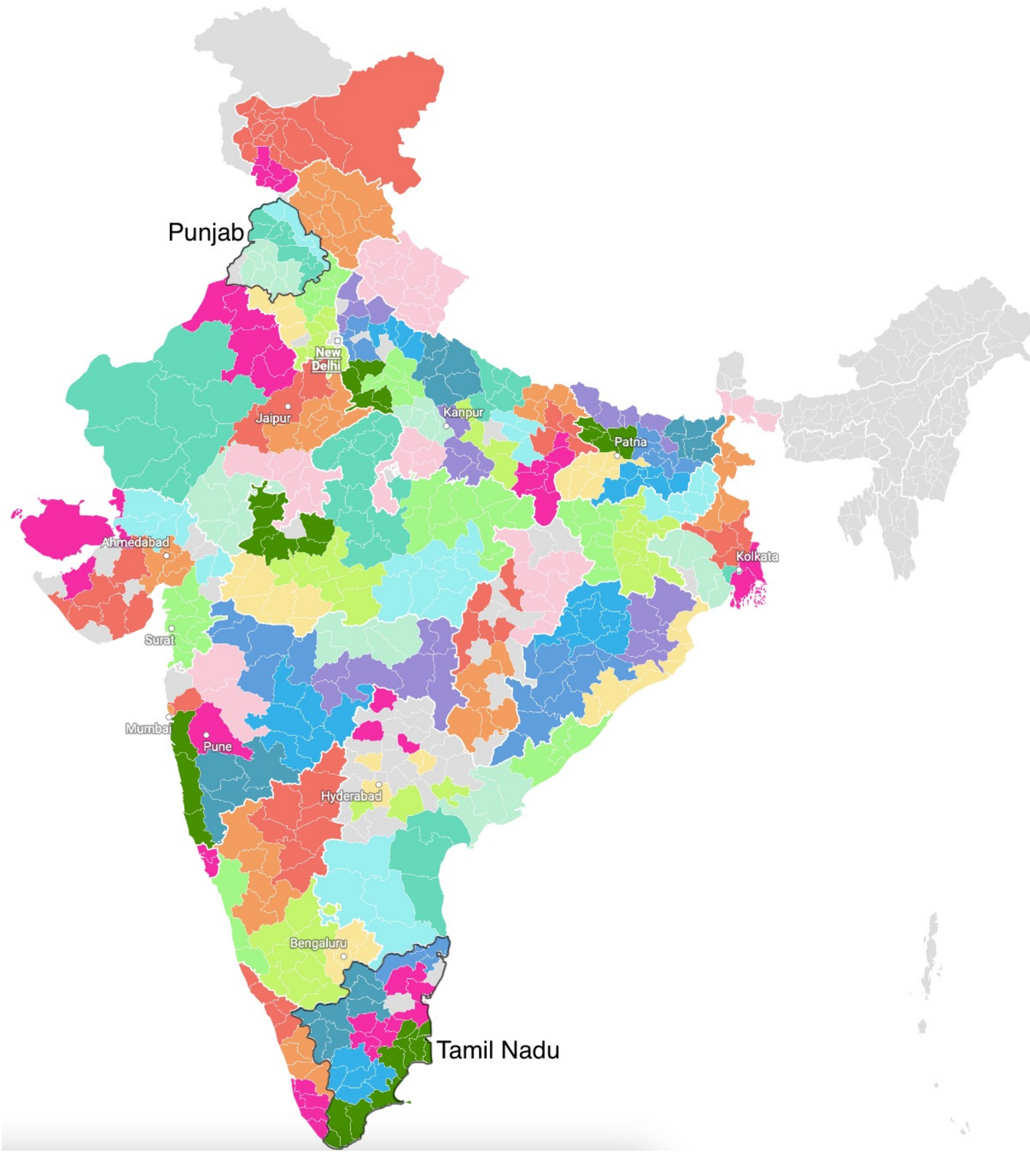
TABLE D14: Impact on Time Use Among **Married Women Employed at Baseline**, by Education (Remove the Delta Wave)

	(1) Travel Time	(2) Time for HH	(3) Time for Work
Treat × Post (TP)	-0.170**	0.154	-0.058
	(0.065)	(0.180)	(0.292)
Treat × Post × Low-education (TPL)	-0.228***	0.688***	-0.421
	(0.063)	(0.167)	(0.290)
Treat × Post × Medium-education (TPM)	-0.094	0.614***	-0.412
	(0.059)	(0.216)	(0.297)
TP+TPL	-0.398***	0.842***	-0.479***
SE	(0.044)	(0.115)	(0.117)
p-value	[0.000]	[0.000]	[0.001]
TP+TPM	-0.264***	0.769***	-0.470***
SE	(0.036)	(0.135)	(0.096)
p-value	[0.000]	[0.000]	[0.000]
Individual FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Treated Mean	0.71	3.32	7.31
R^2	0.45	0.49	0.50
No. of Individuals	6,552	6,552	6,552
N	32,071	32,071	26,846

Notes: We restrict the sample to employed married women and drop the 23rd wave (May-August 2021). In this table, women are categorized by their employment status and education level in the pre-period, with employment defined as being employed in the last sampled period prior to the policy. The omitted group is the high-education women who have bachelor's degrees or above. "Low-education" = Women who went to primary schools or received no education. "Medium-education" = Women who went to middle school, secondary schools, or higher secondary schools. "Time for HH" = Time spent on household activities. "Travel Time" = Time spent on travel. "Time for Work" = Time spent on work done for the employer. All regressions include individual and quarter/wave fixed effects, as well as control for the average number of daily new confirmed cases as a share of the population. All units are hours per day. The treated mean is hours per day and is the average for employed married women in treated states during pre-periods. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

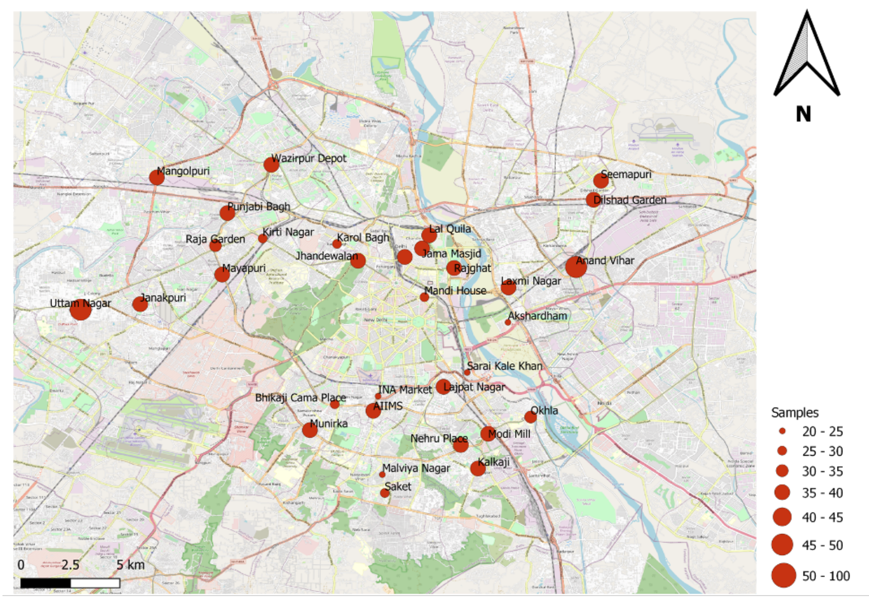
E Additional Figures

FIGURE E1: Map of Homogeneous Regions



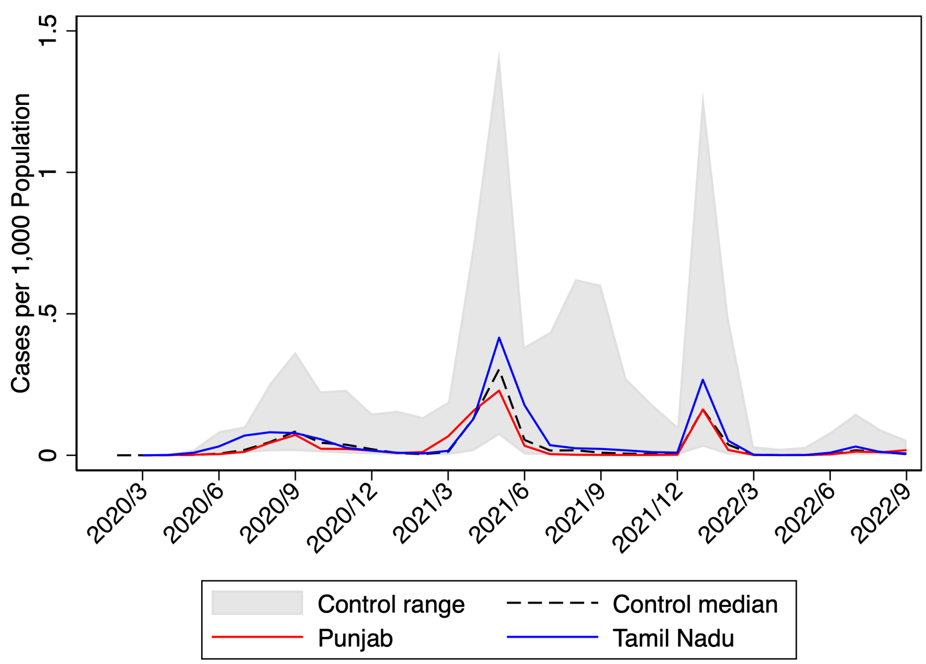
Notes: In this map, we depict the homogeneous regions used in the analysis. Each homogeneous region is represented by a group of districts within a state sharing the same color. The two treated states, Punjab and Tamil Nadu, are labeled, with black lines marking their state borders. They contain three and five homogeneous regions, respectively. In total, there are 96 homogeneous regions, with 8 in the two treated states and 88 across 20 control states and union territories including Andhra Pradesh, Bihar, Chandigarh, Chhattisgarh, Goa, Gujarat, Haryana, Himachal Pradesh, Jammu & Kashmir, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Odisha, Rajasthan, Telangana, Uttar Pradesh, Uttarakhand, and West Bengal. The light gray areas represent districts that are either not used in the analysis or not included in the Consumption Pyramids Household Survey (CPHS). A complete list of homogeneous regions is available on the CPHS website.

FIGURE E2: Map of Delhi Sample Locations



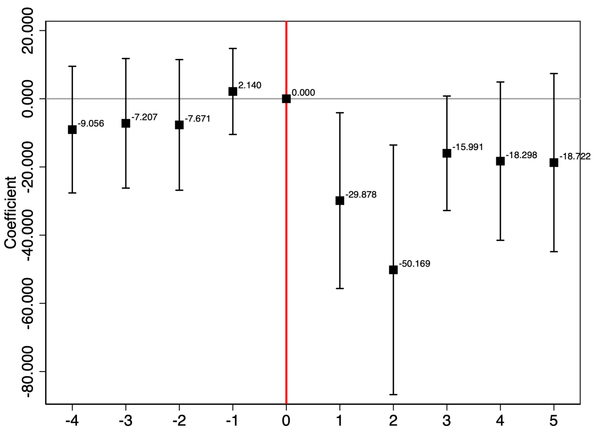
Notes: Each red dot on the map indicates a sample location, with the size of the dot representing the number of women surveyed at that location. Bigger dots indicate a larger number of women surveyed in that particular location. The map is from (Mahendru, 2022).

FIGURE E3: Average Monthly Daily New Confirmed Cases per 1,000 Population by State

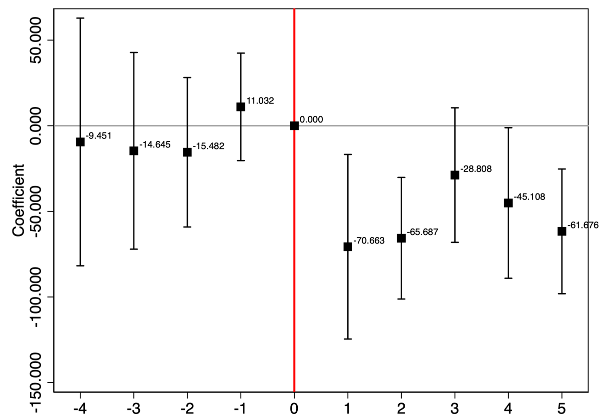


Notes: The figure shows trends in average monthly daily new confirmed COVID-19 cases per 1,000 population across 22 Indian states from March 2020 to September 2022. The gray shaded area represents the range of values for the 20 control states, while the black dashed line indicates their median. The red line shows the trend for Punjab, and the blue line shows the trend for Tamil Nadu.

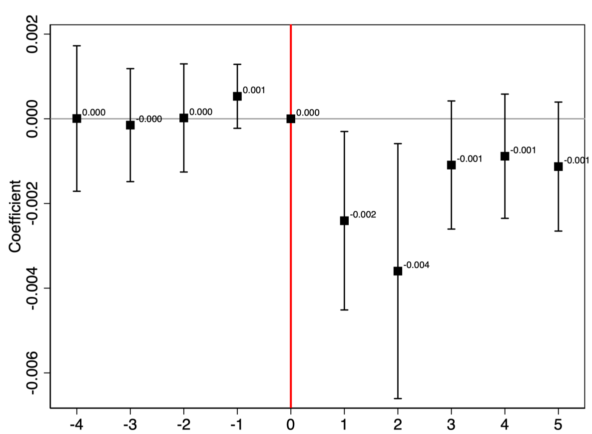
FIGURE E4: Event Study Graphs: Monthly Household Transportation Expenditure



(a) BTF



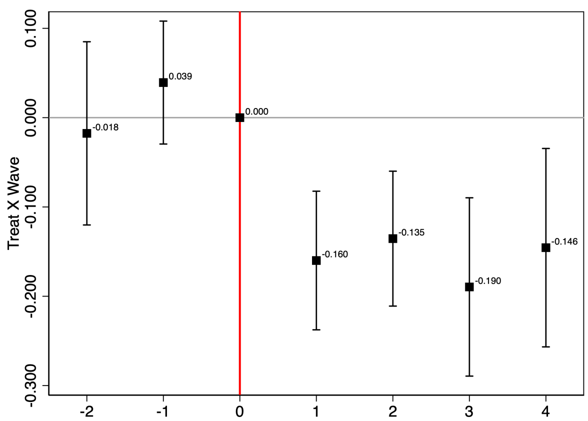
(b) Transport



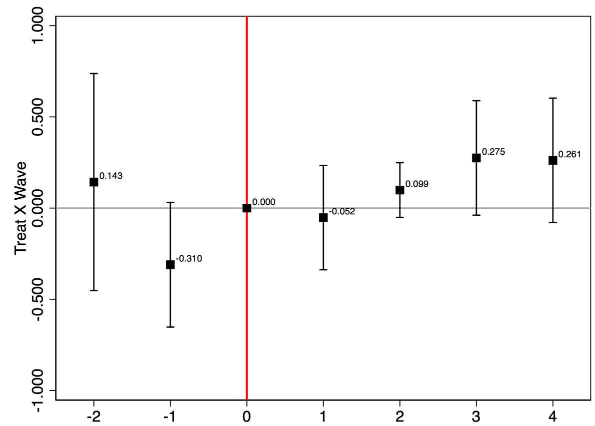
(c) BTF/Expenditure

Notes: "BTF" = Monthly household expenditure on daily bus/train/ferry fare. "Transport" = Total monthly household expenditure on transport. "Expenditure" = Total monthly household expenditure. We analyze the sample of households that are also presented in the PoI data. The time unit of analysis is monthly and $t = 0$ is one month before the program starts. The program started in April and May 2021 in Punjab and Tamil Nadu, respectively. The period of analysis is November 2020-August 2021 for Punjab and December 2020-September 2021 for Tamil Nadu. All regressions include household and month fixed effects and control for the average number of daily new confirmed cases as a share of the population. Standard errors are clustered at the state level. Confidence intervals are at the 95 percent level.

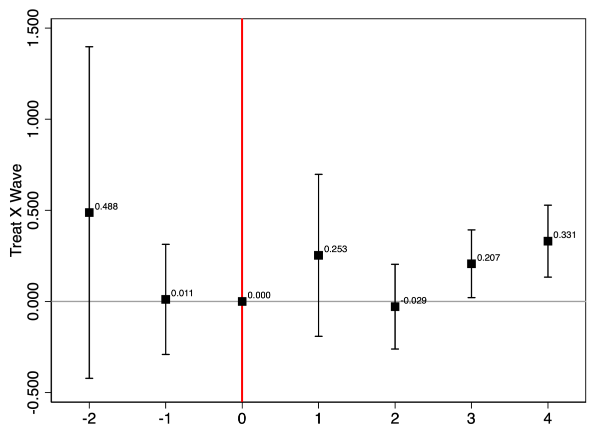
FIGURE E5: Event Study Graphs: Time Usage Among **Women Employed at Baseline**



(a) Travel Time



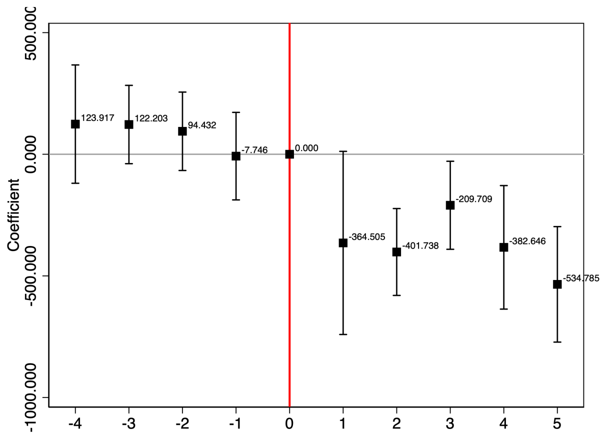
(b) Time for HH



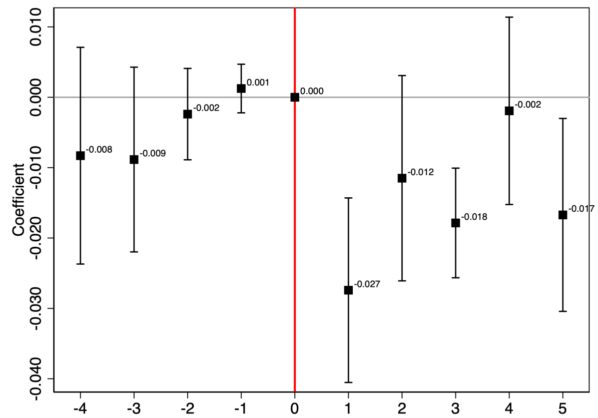
(c) Time for Work

Notes: We restrict the sample to women who were employed in the last sampled period before the policy. Here, $t = 0$ represents one wave (four months) before the program. The program started in April and May 2021 in Punjab and Tamil Nadu, respectively. The time period of analysis here is May-August 2020 to May-August 2022 for both Punjab and Tamil Nadu. The regression includes individual and wave fixed effects, as well as control for the average number of daily new confirmed cases as a share of the population. All units are hours per day. Standard errors are clustered at the state level. Confidence intervals are at the 95 percent level. The estimated coefficients for the two pre-periods are not jointly significant at the 10% level in Figure E5c ($p = 0.22$).

FIGURE E6: Event Study Graphs: Monthly Household Food Expenditure



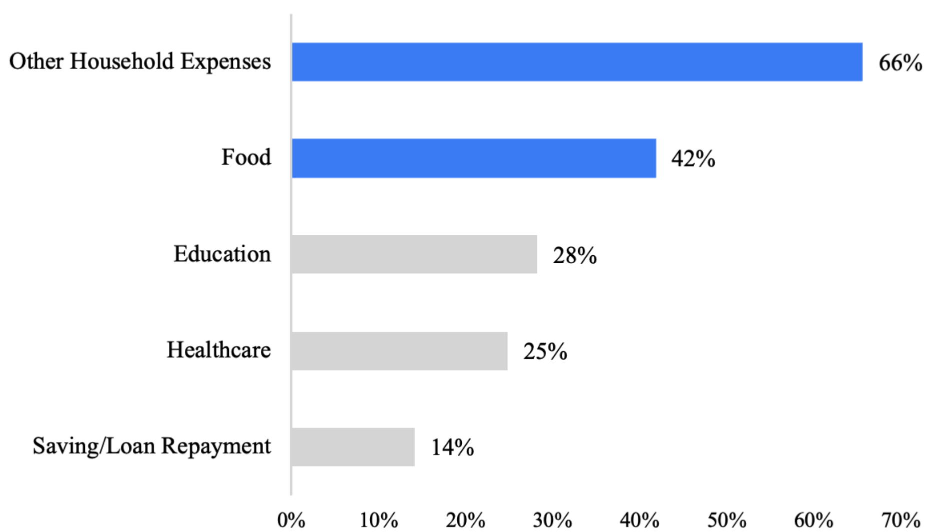
(a) Food



(b) Food/Expenditure

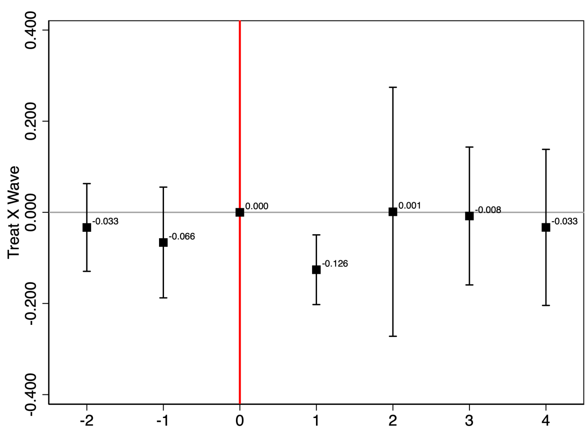
Notes: We analyze the sample of households that also appear in the PoI data. Figure E6a corresponds to column 1 of Table F14 and Figure E6b corresponds to column 3 of Table F14. "Food" = Total monthly household expenditure on all food items. "Expenditure" = Total monthly household expenditure. The time unit of analysis is monthly and $t = 0$ is one month before the program starts. The program started in April and May 2021 in Punjab and Tamil Nadu, respectively. The period of analysis is November 2020-August 2021 for Punjab and December 2020-September 2021 for Tamil Nadu. All regressions include household and month fixed effects and control for the average number of daily new confirmed cases as a share of the population. Standard errors are clustered at the state level. Confidence intervals are at the 95 percent level.

FIGURE E7: Top Five Spending Categories for Savings from Free Bus Travel (CAG Survey Data)

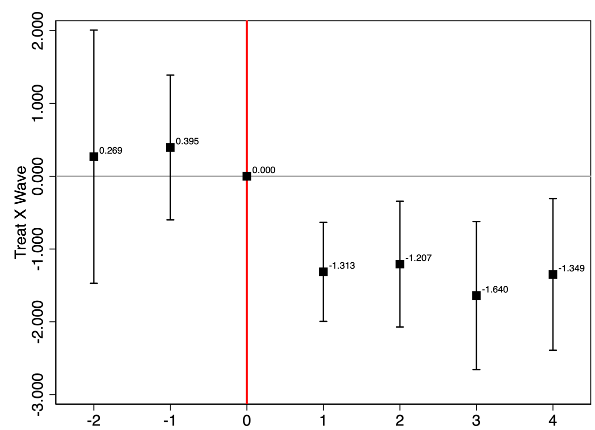


Notes: The survey data is from the Citizen Consumer and Civic Action Group (CAG) (Narayanan, 2024). The survey asked respondents what they used the money saved from the free bus program for, and respondents could select multiple options. We display the top five most frequently chosen categories in this figure: other household expenses, food, education, healthcare, and savings or loan repayment.

FIGURE E8: Event Study Graphs: Time Usage Among **Women Unemployed at Baseline**



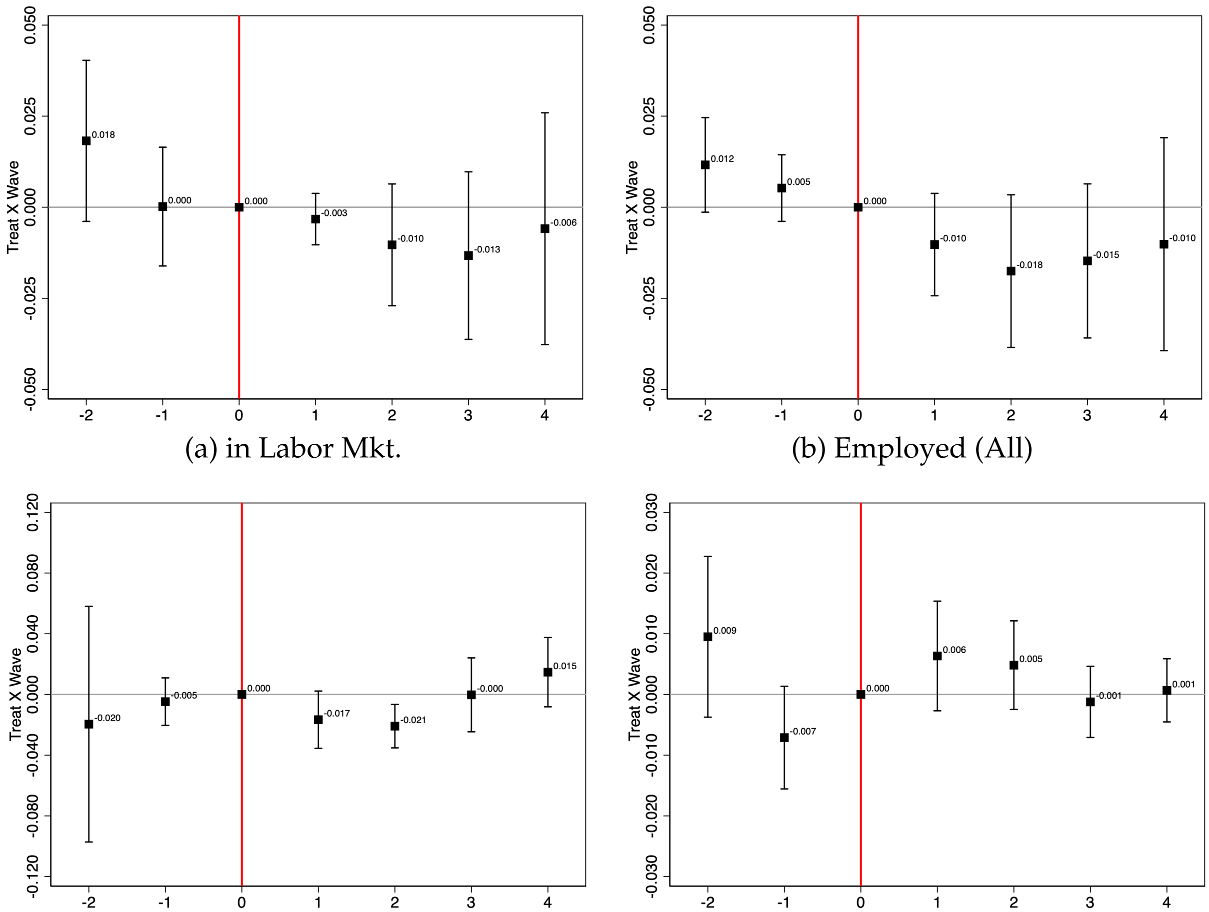
(a) Travel Time, Unemployed



(b) Time for HH, Unemployed

Notes: We restrict the sample to women who are unemployed but actively seeking employment. We categorize women by their pre-period employment status. Here, $t = 0$ represents one wave (four months) before the program. The program started in April and May 2021 in Punjab and Tamil Nadu, respectively. The time period of analysis here is May-August 2020 to May-August 2022 for both Punjab and Tamil Nadu. The regression includes individual and wave fixed effects, as well as controls for the average number of daily new confirmed cases as a share of the population. All units are hours per day. Standard errors are clustered at the state level. Confidence intervals are at the 95 percent level.

FIGURE E9: Event Study Graphs: Labor Market Status for **Women**



(a) in Labor Mkt.

(b) Employed (All)

(c) Employed

(d) Job Search (Not Employed)

Notes: "in Labor Mkt." = A dummy takes the value of one if a member is employed or is unemployed but is looking for a job; it takes the value of zero if a member is unemployed and is neither willing nor looking for a job. "Employed (All)" = A dummy takes the value of one if a woman is employed and zero if a woman is either unemployed but actively seeking a job or out of the labor market. "Employed" = A dummy takes the value of one if a woman is employed and zero if a woman is unemployed and is looking for a job. "Job Search (Not Employed)" = A dummy takes the value of one if a woman is searching for jobs and zero if a woman is out of the labor market. The time unit of analysis is one wave (four-month). Here, $t = 0$ represents one wave (four months) before the program. The program started in April and May 2021 in Punjab and Tamil Nadu, respectively. The time period of analysis here is May-August 2020 to May-August 2022 for both Punjab and Tamil Nadu. The regression includes individual and wave fixed effects, as well as control for the average number of daily new confirmed cases as a share of the population. Standard errors are clustered at the state level. Confidence intervals are at the 95 percent level. The estimated coefficients for the two pre-periods are not jointly significant at the 10% level in Figure E9d ($p = 0.20$).

F Additional Tables

TABLE F1: States With a Free Bus Program for Women

State	Implementation Time
Delhi	November 2019 (The Pink Slip Scheme)
Punjab	**April 2021**
Tamil Nadu	**May 2021**
Puducherry	March 2023
Karnataka	June 2023 (The Shakti Scheme)
Odisha	October 2023 (Concessional fares for women, students, and people with disabilities)
Telangana	December 2023 (The Maha Lakshmi Scheme)
Andhra Pradesh	August 2024
Bihar	August 2024 (In Patna only)
Uttar Pradesh	August 2024 (For women over 60)

Notes: In the table, we list the states that have implemented a free bus program for women chronologically. Those used in the main analysis are in bold. The information is as of December 2024.

TABLE F2: Definition of Time Periods in CP, PoI & InP

Panel A. Consumption Pyramids (CP)				
	$Time_t$	Punjab	Tamil Nadu	$Post_t$
	-4	2020/11	2020/12	0
	-3	2020/12	2021/1	0
	-2	2021/1	2021/2	0
	-1	2021/2	2021/3	0
	0	2021/3	2021/4	0
	1	**2021/4**	**2021/5**	1
	2	2021/5	2021/6	1
	3	2021/6	2021/7	1
	4	2021/7	2021/8	1
	5	2021/8	2021/9	1
Panel B. People of India (PoI))				
No. of Wave	$Time_t$	Punjab & Tamil Nadu		$Post_t$
20	-2	May-Aug 2020		0
21	-1	Sept-Dec 2020		0
22	0	Jan-Apr 2021		0
23	1	**May-Aug 2021**		1
24	2	Sept-Dec 2021		1
25	3	Jan-Apr 2022		1
26	4	May-Aug 2022		1

Notes: The time unit in the CP and InP data is a month, while in the PoI data, it is a wave (four months). To ensure consistency with the time usage analysis using the PoI data, we aggregate the InP data to the wave level (four months). The red time period indicates when the event (*Pink Slip* program) begins.

TABLE F3: Definition of Variables

Variable Name	Definition
Household expenditure	
Expenditure	Total monthly household expenditure which includes expenditure on food, transport, entertainment, and others.
Transport	Monthly household expenditure on transport. It includes daily bus, train, and ferry fares, auto-rickshaw or taxi fares, outstation bus or train fares, parking fees, toll charges, and airfare.
BTF	Monthly household expenditure on daily bus, train, and ferry. It includes fares paid for by both public and private modes of transport.
Food	Monthly household expenditure on all food items.
Time use	
Time for HH	Average daily time spent on household activities including cooking food for household members and taking care of children.
Time for Work	Average daily time spent on income-generating work, including self-employment and salaried jobs.
Travel Time	Average daily time spent traveling from one place to another for shopping, working, school, and others via all kinds of transportation.
Labor market participation & Employment	
in Labor Mkt.	A dummy variable is equal to one if an individual is either employed or unemployed but is willing to work or is looking for a job and zero otherwise. This variable is defined separately for the pre- and post-periods.
Employed (All)	A dummy variable is equal to one if an individual is employed and zero if an individual is either unemployed or out of the labor market.
Employed	A dummy variable is equal to one if an individual is employed and zero if an individual is in the labor market but unemployed.
Job Search (Not Employed)	A dummy variable is equal to one if she is unemployed and is looking for a job and zero if an individual is out of the labor market. This variable is defined separately for the pre- and post-periods.
Education	
Primary	A dummy variable equal to one if an individual has gone to a primary school and zero otherwise.
Middle	A dummy variable equal to one if an individual has gone to a middle school and zero otherwise.
High	A dummy variable equal to one if an individual has gone to a secondary school or a higher secondary school and zero otherwise.
$\geq$Bachelor	A dummy variable is equal to one if an individual has at least a bachelor's degree and zero otherwise.
Grouped Education	
Low-education	A dummy variable equal to one if an individual has gone to primary schools or received no education and zero otherwise.
Medium-education	A dummy variable equal to one if an individual has gone to a middle school, a secondary school, or a higher secondary school and zero otherwise.
Marital status	
Married	A dummy variable is equal to one if an individual is married and zero if an individual is divorced, unmarried, or widowed.

TABLE F4: Summary Statistics: Consumer Pyramids Household Survey

	(1) Control		(2) Treated		t-test Difference
Variable	N	Mean/SD	N	Mean/SD	(1)-(2)/SE
Panel A. Household, December 2020					
Rural	78,067	0.302	6,308	0.291	0.011*
		(0.459)		(0.454)	(0.006)
Number of household members					
1∼3	78,067	0.341	6,308	0.519	-0.179***
		(0.474)		(0.500)	(0.006)
4∼6	78,067	0.278	6,308	0.143	0.135***
		(0.448)		(0.350)	(0.006)
≥7	78,067	0.382	6,308	0.338	0.044***
		(0.486)		(0.473)	(0.006)
Annual income of households					
≤₹200,000	78,067	0.391	6,308	0.437	-0.047***
		(0.488)		(0.496)	(0.006)
200,000∼₹400,000	78,067	0.298	6,308	0.259	0.039***
		(0.458)		(0.438)	(0.006)
≥₹400,000	78,067	0.311	6,308	0.304	0.007
		(0.463)		(0.460)	(0.006)
Monthly household expenditure					
Expenditure	78,067	12,614.979	6,308	13,458.054	-843.08***
		(5731.361)		(5460.394)	(74.762)
Transport	78,067	310.991	6,308	415.710	-104.719***
		(1078.513)		(324.089)	(13.629)
BTF	78,067	77.195	6,308	129.193	-51.998***
		(123.770)		(124.564)	(1.621)
Panel B. Women, May-August 2020					
Age	86,662	35.471	7,016	37.559	-2.088***
		(12.338)		(12.544)	(0.153)
Married	86,662	0.710	7,016	0.700	0.010*
		(0.454)		(0.459)	(0.006)
Education					
≤ Primary	86,662	0.212	7,016	0.185	0.026***
		(0.409)		(0.389)	(0.005)
Middle	86,662	0.220	7,016	0.205	0.015***
		(0.414)		(0.403)	(0.005)
High	86,662	0.422	7,016	0.472	-0.051***
		(0.494)		(0.499)	(0.006)
≥ Bachelor	86,662	0.083	7,016	0.135	-0.052***
		(0.276)		(0.342)	(0.003)
Labor market participation					
in Labor Mkt.	86,662	0.105	7,016	0.098	0.007**
		(0.307)		(0.297)	(0.004)

Table F4 continued from previous page

Variable	(1) Control N	(1) Control Mean/SD	(2) Treated N	(2) Treated Mean/SD	t-test Difference (1)-(2)/SE
Employed	9,107	0.575	683	0.682	-0.106***
		(0.494)		(0.466)	(0.020)
Time usage					
Time for HH	86,662	4.734	7,016	6.367	-1.632***
		(2.526)		(2.807)	(0.032)
Travel Time	86,662	0.171	7,016	0.113	0.059***
		(0.382)		(0.272)	(0.004)
Time for Work	9,107	3.545	683	4.796	-1.251***
		(3.512)		(3.784)	(0.140)

Notes: "Expenditure" = Total monthly household expenditure. "Transport" = Total monthly household expenditure on transport. "BTF" = Monthly household expenditure on daily bus/train/ferry fare. "in Labor Mkt." = A dummy takes the value of one if a member is employed or is unemployed but is looking for a job; it takes the value of zero if a member is unemployed and is neither willing nor looking for a job. "Employed" = A dummy takes the value of one if a member is employed and zero if a member is unemployed and is looking for a job. "Time for HH" = Time spent on household activities. "Time for Work" = Time spent on work done for the employer. "Travel Time" = Time spent on travel. In the last column, we test the differences between treated and control areas using a t-test with equal variance. Statistical significance is indicated as follows: * is $p<0.1$, ** is $p<0.05$, and *** is $p<0.01$.

TABLE F5: Summary Statistics: Delhi Primary Survey (Individual Level)

Variable	(1) Non-users N	(1) Non-users Mean/SD	(2) Users N	(2) Users Mean/SD	t-test Difference (1)-(2)/SE
Age group					
15∼20	500	0.112	1,525	0.119	-0.007
		(0.316)		(0.324)	
21∼30	500	0.592	1,525	0.392	0.200***
		(0.492)		(0.488)	
31∼40	500	0.182	1,525	0.336	-0.154***
		(0.386)		(0.473)	
41∼50	500	0.114	1,525	0.136	-0.022
		(0.318)		(0.343)	
>50	500	0.000	1,525	0.016	-0.016***
		(0.000)		(0.124)	
Occupation					
Student	500	0.056	1,525	0.301	-0.245***
		(0.230)		(0.459)	
Business	500	0.014	1,525	0.068	-0.054***
		(0.118)		(0.252)	
Daily wager	500	0.068	1,525	0.047	0.021*
		(0.252)		(0.211)	

Table F5 continued from previous page

	(1) Non-users		(2) Users		t-test Difference
Variable	N	Mean/SD	N	Mean/SD	(1)-(2)/SE
Informal worker	500	0.130 (0.337)	1,525	0.044 (0.205)	0.086***
Service	500	0.632 (0.483)	1,525	0.283 (0.451)	0.349***
Homemaker	500	0.100 (0.300)	1,525	0.257 (0.437)	-0.157***
Total average monthly household income					
₹0∼₹10,000	500	0.088 (0.284)	1,525	0.005 (0.072)	0.083***
₹10,001∼₹20,000	500	0.474 (0.500)	1,525	0.092 (0.290)	0.382***
₹20,001∼₹40,000	500	0.384 (0.487)	1,525	0.450 (0.498)	-0.066***
>₹40,000	500	0.054 (0.226)	1,525	0.452 (0.498)	-0.398***
Travel Purpose					
Education	500	0.062 (0.241)	1,525	0.280 (0.449)	-0.218***
Healthcare	500	0.020 (0.140)	1,525	0.050 (0.218)	-0.030***
Leisure	500	0.060 (0.238)	1,525	0.089 (0.284)	-0.029**
Religious	500	0.018 (0.133)	1,525	0.129 (0.336)	-0.111***
Shopping	500	0.034 (0.181)	1,525	0.065 (0.246)	-0.031***
Work	500	0.806 (0.396)	1,525	0.365 (0.481)	0.441***

Notes: All variables are indicator variables. In the last column, we test the differences between treated and control areas using a t-test with equal variance. Statistical significance is indicated as follows: * is $p<0.1$, ** is $p<0.05$, and *** is $p<0.01$.

TABLE F6: Summary Statistics: CAG Survey (Individual Level)

Variable	Observations	Mean	SD
Age group			
18∼20	2,330	0.137	0.343
21∼30	2,330	0.312	0.463
31∼40	2,330	0.304	0.46
41∼50	2,330	0.248	0.432
Profession			
Employed	2,330	0.633	0.482
Unemployed	2,330	0.051	0.22
Student	2,330	0.176	0.381
Homemaker	2,330	0.139	0.346
Retired	2,330	0.001	0.036
Monthly Income			
<₹5,000	2,322	0.098	0.298
₹5,001∼₹10,000	2,322	0.307	0.461
₹10,001∼₹20,000	2,322	0.182	0.386
₹20,001∼₹40,000	2,322	0.067	0.25
₹40,001∼₹60,000	2,322	0.023	0.149
₹60,001∼₹100,000	2,322	0.013	0.113
No Income	2,322	0.311	0.463

Notes: "Employed" = A dummy variable equal to one if the woman selected one of the following professions: security/watchwoman, self-employed, small-scale industry, MSME and construction work, or working professional. All variables are indicator variables. We restrict the sample to women aged between 18 and 50.

TABLE F7: Impact on Household Transportation Expenditures: HR-Level Data with SDID and Different Inference Methods

	(1) BTF	(2) Transport	(3) BTF/Transport	(4) BTF/Expenditure
Treat × Post	-26.569	-52.636	-0.091	-0.002
Bootstrap SE	(13.008)**	(23.602)**	(0.037)**	(0.001)*
Jackknife SE	(13.370)**	(28.563)*	(0.036)**	(0.001)*
Placebo SE	(13.076)**	(17.328)***	(0.054)*	(0.001)
No. of HRs	96	96	96	96
No. of Time Periods	10	10	10	10

Notes: This table replicates Table 2 in the main text. However, here we aggregate household-level data to the homogeneous region level and then directly apply the synthetic difference-in-differences method (Arkhangelsky et al., 2021) to the homogeneous-region panel data. In total, we have 96 homogeneous regions in 22 Indian states. "BTF" = Monthly household expenditure on daily bus/train/ferry fare. "Transport" = Total monthly household expenditure on transport. "Expenditure" = Total monthly household expenditure. Standard errors are reported using three inference procedures: bootstrap, jackknife, and placebo. Statistical significance is indicated as follows: * is $p<0.1$, ** is $p<0.05$, and *** is $p<0.01$.

TABLE F8: Impact on Time Use Among **All Women**

	(1) Travel Time	(2) Time for HH
Treat × Post	-0.065	-0.363
	(0.081)	(0.224)
Individual FE	Yes	Yes
Wave FE	Yes	Yes
Treated Mean	0.13	6.01
R^2	0.51	0.76
No. of Individuals	197,760	197,760
N	981,668	981,668

Notes: We use all women in this table."Time for HH" = Time spent on household activities. "Travel Time" = Time spent on travel. All regressions include individual and quarter/wave fixed effects, as well as control for the average number of daily new confirmed cases as a share of the population. All units are hours per day. The treated mean is hours per day and is the average for women in pre-periods and treated states. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

TABLE F9: Impact on Time Use Among Women Employed at Baseline (Same Set of Observations)

	(1) Travel Time	(2) Time for HH	(3) Time for Work
Panel A. Employed Women			
Treat × Post	-0.138***	0.201***	0.114*
	(0.034)	(0.054)	(0.056)
R^2	0.45	0.56	0.46
Panel B. Employed Women By Education			
Treat × Post (TP)	-0.052	-0.197	0.266***
	(0.060)	(0.140)	(0.092)
Treat × Post × Low-education (TPL)	-0.196***	0.698***	-0.519***
	(0.052)	(0.173)	(0.141)
Treat × Post × Medium-education (TPM)	-0.052	0.355**	-0.032
	(0.057)	(0.154)	(0.110)
TP+TPL	-0.248***	0.502***	-0.253**
SE	(0.036)	(0.077)	(0.090)
p-value	[0.000]	[0.000]	[0.011]
TP+TPM	-0.104***	0.158***	0.234***
SE	(0.029)	(0.055)	(0.067)
p-value	[0.000]	[0.009]	[0.002]
R^2	0.45	0.56	0.47
Individual FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Treated Mean	0.68	2.81	7.34
No. of Individuals	11,454	11,454	11,454
N	47,718	47,718	47,718

Notes: In this table, we ensure that the same set of individual–wave observations is used in each column. We categorize women based on their employment status and education level during the pre-period, with employment defined as being employed in the last sampled period prior to the policy. Note that column (3) of Table 3 is not shown here because the outcome variable "out Labor Mkt." equals zero for all observations. The omitted group is the employed high-education women who have bachelor's degrees or above in panel B. "Travel Time" = Time spent on travel. "Time for HH" = Time spent on household activities. "Time for Work" = Time spent on work done for the employer. "Low-education" = Women who went to primary schools or received no education. "Medium-education" = Women who went to middle school, secondary schools, or higher secondary schools. All regressions include individual and quarter/wave fixed effects, as well as control for the average number of daily new confirmed cases as a share of the population. All units are hours per day. The treated mean is hours per day and is the average for employed women in treated states during pre-periods. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

TABLE F10: Share of Women by Education

		Post-periods			
		Low-educ.	Medium-educ.	High-educ.	Total
Pre-periods	Low-educ.	97.0%	3.0%	0.0%	100.0%
	Medium-edu.	0.0%	100.0%	0.0%	100.0%
	High-educ.	0.0%	0.0%	100.0%	100.0%

Notes: The table presents the proportion of women who belong to a specific education group and continue to be part of the same group in the post-periods. For example, around 97% of women who were classified as low-education during the pre-periods maintained their low-education status in the post-periods.

TABLE F11: Share of Women by Marital Status

		Post-periods		
		Unmarried	Married	Total
Pre-periods	Unmarried	93.0%	7.0%	100.0%
	Married	1.7%	98.3%	100.0%

Notes: The table displays the proportion of women who were (un)married in the pre-periods and remained (un)married in the post-periods. For instance, approximately 97% of women who were married during the pre-periods remained married in the post-periods.

TABLE F12: Impact on Food Expenditures for Households with Married Women Employed at Baseline (Remove the Delta Wave)

	(1) All Educ. Levels	(2) Low Educ.	(3) Medium Educ.	(4) High Educ.
Panel A. Dependent Variable = Food Expenditure				
Treat × Post	-706.049***	-394.878***	-828.042***	-667.725***
	(173.879)	(109.331)	(248.390)	(71.326)
Treated Mean	5720.21	5208.77	5791.39	6775.61
R^2	0.81	0.80	0.78	0.87
Panel B. Dependent Variable = Food/Expenditure				
Treat × Post	0.006	0.012	0.008	-0.034***
	(0.009)	(0.012)	(0.009)	(0.010)
Treated Mean	0.50	0.52	0.51	0.43
R^2	0.69	0.68	0.66	0.80
HH FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes
No. of HHs	7,424	2,725	3,880	784
N	39,812	13,952	21,253	4,355

Notes: This table replicates Table 8 in the main text by changing the post-policy periods. We exclude the first two post-periods. We conduct the analysis on the sample of households that are also represented in the individual-level data. The dependent variable is the monthly household expenditure on all food items ("Food") in Panel A and is the monthly household expenditure on food as a share of total monthly household expenditure ("Food/Expenditure") in Panel B. Column 1 includes **households with employed married women**; column 2 include **those with low-education employed married women**; column 3 include **households with medium-education employed married women**; and column 4 includes **those with high-education employed married women**. The number of households reported in columns 2–4 does not necessarily add up to the number of households in column 1, as a household may include multiple employed married women with different education levels. All regressions include household and month fixed effects and control for the average number of daily new confirmed cases as a share of the population. The unit of outcome variables is Indian Rupees in Panel A. The treated mean is the average for households in treated states and pre-periods. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

TABLE F13: Impact on Total Expenditures for Households with Married Women Employed at Baseline

	(1) All Educ. Levels	(2) Low Educ.	(3) Medium Educ.	(4) High Educ.
Panel A. Baseline				
Treat × Post	-849.100***	-628.783***	-1086.820***	798.090*
	(279.759)	(177.309)	(334.647)	(458.123)
Treated Mean	10519.54	9092.13	10123.39	16151.02
R^2	0.77	0.77	0.69	0.79
No. of HHs	7,522	2,769	3,926	791
N	49,126	17,348	26,208	5,264
Panel B. Remove the Delta Wave				
Treat × Post	-915.499***	-609.734***	-1157.458***	337.715
	(314.211)	(203.942)	(361.131)	(599.822)
Treated Mean	10516.91	9092.13	10123.39	16156.53
R^2	0.77	0.77	0.70	0.78
No. of HHs	7,424	2,725	3,880	784
N	39,812	13,952	21,253	4,355
HH FE	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes

Notes: We conduct the analysis on the sample of households that are also represented in the individual-level data. The dependent variable is the total monthly household expenditure. Column 1 includes **households with employed married women**; column 2 includes **households with low-education employed married women**; column 3 includes **those with medium-education employed married women**; and column 4 includes **households with high-education employed married women**. In Panel B, we exclude April and May 2021 for Punjab and May and June 2021 for Tamil Nadu. Meanwhile, we include September and October 2021 for Punjab and October and November 2021 for Tamil Nadu. All regressions include household and month fixed effects and control for the average number of daily new confirmed cases as a share of the population. The unit of outcome variables is Indian Rupees. The treated mean is the average for households in treated states and pre-periods. The number of households reported in columns 2–4 does not necessarily add up to the number of households in column 1, as a household may include multiple employed married women with different education levels. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

TABLE F14: Impact on Food Expenditures for Households with Women

	(1) Food Expenditure	(2) Total Expenditure	(3) Food/Total
Panel A. Baseline			
Treat × Post	-504.354***	-190.650	-0.013***
	(89.059)	(183.040)	(0.004)
Treated Mean	5874.54	12420.09	0.47
R^2	0.78	0.69	0.74
No. of HHs	115,745	115,745	115,745
N	785,868	785,868	785,868
Panel B. Remove the Delta Wave			
Treat × Post	-441.055***	-234.165	-0.012**
	(113.578)	(230.928)	(0.005)
Treated Mean	5875.45	12418.07	0.47
R^2	0.81	0.68	0.75
No. of HHs	114,936	114,936	114,936
N	639,375	639,375	639,375
HH FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes

Notes: We conduct the analysis on the sample of households that are also represented in the individual-level data. "Food Expenditure" = Monthly household expenditure on all food items. "Total Expenditure" = Total monthly household expenditure. "Food/Total" = The monthly household expenditure on food as a share of total monthly household expenditure. In Panel B, we exclude April and May 2021 for Punjab and May and June 2021 for Tamil Nadu. Meanwhile, we include September and October 2021 for Punjab and October and November 2021 for Tamil Nadu. All regressions include household and month fixed effects and control for the average number of daily new confirmed cases as a share of the population. The unit of outcome variables is Indian Rupees in columns 1-2. The treated mean is the average for households in treated states and pre-periods. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is $p<0.1$, ** is $p<0.05$, and *** is $p<0.01$.

TABLE F15: Impact on Labor Market Status for Women

	(1) in Labor Mkt.	(2) Employed (All)	(3) Employed	(4) Job Search (Not Employed)
Panel A.				
Treat × Post	-0.009	-0.014	-0.005	0.003
	(0.009)	(0.010)	(0.007)	(0.005)
R^2	0.84	0.85	0.90	0.72
Panel B. By Marital Status				
Treat × Post (TP)	-0.000	-0.000	-0.003	-0.013
	(0.009)	(0.002)	(0.006)	(0.014)
Treat × Post × Married (TPMa)	-0.012	-0.018	-0.008	0.021
	(0.021)	(0.013)	(0.007)	(0.014)
TP+TPMa	-0.012	-0.018	-0.011	0.008**
SE	(0.014)	(0.013)	(0.009)	(0.003)
p-value	[0.394]	[0.184]	[0.203]	[0.029]
R^2	0.84	0.85	0.90	0.72
Individual FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Treated Mean	0.07	0.06	0.81	0.01
No. of Individuals	198,019	198,019	23,802	186,661
N	982,943	982,943	91,563	913,010

Notes: In columns 1-2, the sample includes both women participating in the labor market and those outside the labor market (i.e., all women). In column 3, the sample is restricted to women in the labor market. Column 4 includes women who are out of the labor market or unemployed. "in Labor Mkt." = A dummy takes the value of one if a member is either employed or unemployed but is looking for a job (i.e., participating in the labor market); it takes the value of zero if a member is not employed and is neither willing nor looking for a job. "Employed (All)" = A dummy takes the value of one if a woman is employed and zero if a woman is either unemployed but actively seeking a job or out of the labor market. "Employed" = A dummy takes the value of one if a woman is employed and zero if a woman is unemployed but is actively looking for a job. "Job Search (Not Employed)" = A dummy takes the value of one if a woman is unemployed and is actively searching for jobs and zero if a woman is unemployed but is neither willing nor looking for a job (i.e., out of the labor market). All regressions include individual and quarter/wave fixed effects, as well as control for the average number of daily new confirmed cases as a share of the population. The treated mean is the share of women belonging to a specific status in treated states during pre-periods. Standard errors are clustered at the state level. Statistical significance is indicated as follows: * is p<0.1, ** is p<0.05, and *** is p<0.01.

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