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 has complex and diverse effects on women's labor dynamics. 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 shed light on labor supply and time use decisions of women. We observe decreased bus expenses and time saved on travel. Skilled employed women increase labor supply, while low-skill married women shift focus to household chores. Unemployed women intensify job searches, yet overall employment rates remain unchanged. Our findings highlight that alleviating commuting costs does not uniformly boost women's labor participation, as gender roles and societal norms continue to shape outcomes.

Keywords: Transport, Gender, Time-Use, Female Labor Force Participation
JEL codes: J16, J22, R41

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1 Introduction

The gender disparity in commuting barriers is pervasive, affecting women in developing and developed nations. Recent OECD findings reveal a substantial gender commuting gap, with men averaging 33.4 minutes per day compared to women's 21.9 minutes, indicating a 31.1% difference (OECD, 2016). Developing countries exhibit even more pronounced patterns; Indian women, on average, spend a mere 8 minutes daily on employment-related travel, compared to men's 36 minutes.[1] The International Labour Organization (2017) reports that lack of transportation decreases women's probability of participating in the labor market by 16.5 percentage points among developing countries. Given the established influence of commuting barriers on women's labor supply, a natural inquiry arises: Can reducing these barriers influence women's labor supply decisions? Whether or not policies directly addressing commuting costs would help increase 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, by utilizing the implementation of a free busing program, the *Pink Slip* program, in two 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 transportation, 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 28.2% of the working-age population as of 2019, significantly lower than the average of 46% in low- and middle-income countries.[2]

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 Novem-

[1] India's 2019 National Time-use Survey (https://mospi.gov.in/time-use-survey).

[2] World Bank's Gender Data portal (https://tinyurl.com/4a8rm5ye). According to the most recent female labor force survey by India's Ministry of Statistics and Program Implementation, it increased to 37% (http://tinyurl.com/mu2vx7m3).

ber 2019, data limitations preclude us from including it in our sample.[3] Several media reports indicate that women's response to the initiative was positive. For example, from July 2021 to March 2022, the percentage of women traveling by bus in Tamil Nadu increased from 40% to 61% (Sundaram, 2022). According to Goswami (2021), women made up the majority of riders on Delhi Transport Corporation buses by March 2021 after the program's launch.

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 time use patterns and allocation of time on various activities. We bolster the findings with a large primary survey of women from Delhi that was collected after the program's launch in Delhi.

Our identification approach compares women in treated states (i.e., Punjab and Tamil Nadu) to their geographical neighbors, serving 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) at the state level. This approach combines the synthetic control method (Abadie and Gardeazabal, 2003) with the difference-in-differences strategy.[4] We compare the pre-trends in our treated and the synthetic control group 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 consistent with elastic demand for transportation for women using the CPHS data. Overall expenditure on travel, specifically on a category that includes buses, was reduced for households with women in treated states compared to those in control states. Findings from the Delhi survey corroborate these results at the individual level. New female bus users report negligible transportation costs after the start of the policy, in contrast to their substantial expenditures on other modes of transport before switching to buses.

[3]The CMIE, our data source in this paper, started collecting information on individual time usage after Delhi started implementing the *Pink Slip* program. So, we are unable to include Delhi in our sample.

[4]The weights from the SDID approach are used in all survey data-based analyses at the individual level.

We then investigate if women in the treated areas change the time spent on traveling and, if they do, the potential reallocation of that time to other margins of time use, such as household chores and labor supply. Diverse outcomes emerge among women in response to the policy change. We scrutinize these nuanced effects along three key dimensions: employment status, skill levels, and marital status. We observe contrasting effects on travel time and time spent on household chores between employed and unemployed women, leading to an overall null effect. Skill levels and marital status significantly influence time allocation: skilled employed women leverage commuting time savings to increase labor hours, while unmarried unemployed women intensify their job searches. However, short-term employment outcomes do not show immediate positive shifts, highlighting women's additional constraints in finding employment.

In contrast to skilled employed women, low-skill workers redirect commuting time towards household chores and reduce their labor hours. This pattern is particularly pronounced among low-skill, married, employed women. We propose a model that implicates household reallocation of activities as a mechanism for this shift. The model illustrates that indivisible chores requiring discrete time can result in intra-household reallocation, where the re-optimization is influenced by the gender wage gap. In support of this theory, married men alter their time use reciprocally: employed individuals increase their labor supply and decrease time spent on domestic work. Hence, our main findings indicate that the free bus initiative benefits skilled and unmarried women. Still, the low-skill married women respond by reducing their labor and increasing their time devoted to household chores. Consistent with restrictive gender norms discussed by Jayachandran (2021) and Dinkelman and Ngai (2022), low-skill married women's labor outcomes become worse, if anything. Without a deeper understanding of these countervailing effects on different populations of women, observing an overall null effect could lead to spurious policy recommendations. We argue that transportation subsidies to women, which might seem to have redistributive merit, do not necessarily help improve the labor market outcomes of all women. Only skilled employed women, who constitute a small share of the workforce, benefit from these types of programs in the short run.

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. 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 in 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. Two projects relate to the Pink Slip Program as well. In the first, Dasgupta and Datta (2023) use a cross-sectional time-use survey and compare women to men across states to assess how the Pink Slip program in Delhi affected women's time-use patterns relative to men. They document an increase of 30 to 50 minutes in women's work time during the first two months after the program's introduction. Aside from a more robust identification strategy, using a rich set of other economic outcomes, our findings also diverge. We find a null causal effect on time use in our panel estimation masked by heterogeneity in employment status. The second is an ongoing project in which Borker et al. (2020) leverage a randomized control trial to compare the partial equilibrium results of free bus passes to the general equilibrium effects of Delhi's policy. We extend this literature by highlighting that demand for transportation is elastic for women, but there is heterogeneity by skill 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 markets.

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. 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. Section 3 details the datasets. Section 4 outlines the empirical methodology used to estimate the impacts of reductions in commuting costs. Section 5 presents the results on changes in expenditure; Section 6 discusses the results on time use; Section 7 examines the results on changes in (un)employment. Finally, Section 8 provides concluding remarks.

2 Background

In India, limited infrastructure and transport services restrict mobility for both men and women. Still, women frequently experience extra socio-cultural and economic factors that negatively affect their commute patterns (Srinivasan and Rogers, 2005; Tripathi et al., 2017; Alam et al., 2021). Given the sizeable gender wage gap (Duraisamy and Duraisamy, 2016; Deshpande et al., 2018) and the additional barriers in accessing the financial system compared to men (Khera, 2018), paid access to transportation is plausibly harder for Indian women. Besides, the low rate of female usage of public transport might raise a perception problem since more female presence in public transportation makes women feel safer (Sajjad et al., 2017). In a survey of 3,800 students at Delhi University, Borker (2021) found that women are willing to travel 27 minutes more per day or 40% more than their daily travel time if they can use a perceived safer transport route. These factors put women at a disadvantage regarding access to transport services and infrastructure (Astrop et al., 1996; Dominguez Gonzalez et al., 2020), potentially affecting their participation in labor markets (Patacchini and Zenou, 2005; ILO, 2017; Sajjad et al., 2017; Martinez et al., 2020).

In light of these challenges, the Delhi government introduced a program offering free bus rides to all women in the city from November 2019 onward (Kejriwal, 2019). The program makes bus travel free for women in all Delhi Transport Corporation (DTC) and Cluster buses. On each ride, bus operators provide a pink ticket to each woman. Afterward, Delhi's government compensates the bus operators with ₹10, the equivalent of $0.14 (all currency conversions use the 11/2019 exchange rate), per pink ticket ride (The Economic Times, 2019; Durai, 2021). The program showed an early response: just 20 days after the program's launch, female daily ridership in DTC and cluster buses increased from 33% to 44%.[5]

Spurred by the good reception of the initiative in Delhi, Punjab and Tamil Nadu launched free bus ride programs for women on April 1 and May 7, 2021, respectively. These programs allow free travel on government-owned public buses in their states.[6] From July 2021 to March 2022, the percentage of women commuting by bus in Tamil Nadu rose from 40% to 61% (Sundaram, 2022).

[5]Refer to this website at https://shorturl.at/cAFMT, last accessed on May 13, 2024.

[6]In Punjab, these include PEPSU Road Transport Corporation (PRTC), PUNBUS, Punjab Roadways Buses, and City Bus Services, but did not include AC buses, Volvo Buses, and HVAC Buses (Express, 2021). In Tamil Nadu, the free ride program includes tickets for the Tamil Nadu State Transport Corporation (TNSTC) ordinary city buses.

3 Data

3.1 Consumer Pyramids Household Survey

Our main data source is the Consumer Pyramids Household Survey (CPHS). It is a household-level longitudinal survey 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 the following characteristics: climate, urbanization, female literacy rate, and population. In Appendix Table D1, we list the two treated states of Punjab and Tamil Nadu–which implemented free bus ride programs for women–and the control states, i.e., the states that are adjacent to the treated states and did not distribute free bus tickets to women.[7] Since the CPHS data is representative at the HR level, our analysis includes only the adjacent HRs in the control states; Non-adjacent HRs in control states are excluded. Appendix Figure C1 displays the map of treated and control HRs. We have 20 HRs in two treatment and seven 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. 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 shows how much time a person spends on household activities, at work, and traveling. Reported time on travel is spent by a person traveling from one

[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.

place to another for various purposes, including work-related activities. The CP section does not ask specific questions about time spent commuting to work, searching for a job, or on leisure activities.

We use six waves of PoI from May-August 2020 to January-April 2022 (or from the 20th to the 25th wave). We also match the households in the PoI data to those in the CP data. Appendix Table D2 lists the study periods for the two sectional data sets. We restrict our sample to women (or households having women) aged between 15 and 65 at their first appearance in the data. Appendix Table D3 lists the variables used in the analysis and their definitions. Appendix Table D4 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 HRs, concerning rural residence, number of people, and per-capita income and expenditures, are relatively small. In panel B, we compare women in treated HRs to those in control HRs in May-August 2020. The distributions of age, marital status, and education are 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.

3.2 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 C2.[8] Appendix Table D5 provides some summary statistics of the survey sample. Compared to non-users, bus users (both new and con-

[8]The generation points are all major locations within the city where trips originate or are attracted to. These include major work areas, shopping districts, and schools.

tinuous) 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,[9] 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 sample is characterized by higher levels of education and annual household income. 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.[10]

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 bus transit; 2) safety regarding accidents, crashes, threats, and thefts; 3) connectivity; 4) bus frequency, waiting time, travel duration, and unnecessary stops; 5) accessibility to bus stops. In panel A, we can see that non-users consistently give lower ratings across all five perspectives; they find bus travel less satisfactory across all five dimensions compared to users. They are particularly concerned about safety issues. The average rating concerning safety among non-users is 1.63, indicating a level of satisfaction that falls between highly unsatisfactory and unsatisfactory. In panel B, we find that compared to continuous users, and new users tend to give a lower rating to safety (0.13 points lower) but higher ratings to affordability and the availability of free commutes. Specifically, new users, on average, rate affordability of buses 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.

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

[10]In contrast, in the CPHS data, about 44% of households in treated states reported an annual household income exceeding ₹200,000 as of December 2020 (panel A of Appendix D4).

3.3 Auxiliary Data

Since our study period overlaps with the COVID-19 pandemic period, we obtain COVID-19 case data from Google Health. We also use the Indian Population Census 2011 to obtain district-level characteristics like population. We combine the two data sets and construct average daily new confirmed cases as a share of the population in a district. We include this variable in our regressions to account for the potential effects of COVID-19 on outcomes like labor market participation. To address further concerns that different states experienced different levels of mobility restrictions, we use data from the Oxford Covid Tracker 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. Apart from including only the neighboring states of the treated state as controls, we employ a synthetic difference-in-differences strategy (SDID) proposed by Arkhangelsky et al. (2021) to allay this concern further. The SDID re-weights the control units to make their time 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. Since, in our setting, the treatment is applied at the state level, we construct a state-level panel using the CPHS data. With this panel, we can derive each control state's SDID unit and time weights. 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 state j and time t weighted by the individual (or household) sampling weight, along with the SDID time and unit weights. Starting with a standard stacked event-study design

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

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

For example, in the household-level data (CP data), $Time = 0$ corresponds to 1 month before the event; in the individual-level data (PoI data), $Time = 0$ corresponds to 1 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. We then pool the pre- and post-treatment periods together to estimate

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

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, encompassing month and year-fixed effects in the regression that examines changes in household consumption. In the analysis of PoI data, α_t comprises wave and year-fixed effects. Appendix Table D2 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 Expenditure

We use both the CPHS data and the Delhi survey to isolate the effect of treatment on transportation expenditure.

5.1 Evidence from The CPHS Data

To examine the impact of the *Pink Slip* program on monthly *household* expenses, we plot the estimated coefficient $\hat{\beta}_t$ from the event-study specification (1) in Figure 1 and detect no pre-trends. However, after implementation, we see a substantial decrease in household expenditure on transportation in the treated states. Treated households report 10.6-37.2 log points lower expenses on all kinds of transport relative to control households after the program was implemented (Figure 1(a)). We also find that the share of transport expense in total expenditure decreased by 0.3-0.6 percentage points (Figure 1(b)). Consistently, we find a reduction in the expenditure on bus/train/ferries category (BTF) as shown in Figure 1(c) and the share of BTF in total transport expenditure also fell as seen in Figure 1(d).

In Table 2, we present the average treatment effects of the program on household expenditures, as estimated using equation (2). Across columns 1 to 5, it is evident that households in Punjab and Tamil Nadu spent considerably less on transportation compared to their counterparts in neighboring states during the post-treatment periods relative to the pre-period. Specifically, following the program implementation, expenditure on BTF as a proportion of total transport expenses for treated households decreased by an average of 6.6 percentage points compared to the control group (column 5).

A concern might be that differences in COVID 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 the house in a month. We present the results in Appendix Table D6. The estimated coefficients remain robust when these controls are added, with magnitudes and standard errors similar to those in the baseline Table 2. Finally, the significance levels of the baseline estimates remain robust when the standard errors are clustered at the district level (see Appendix Table D7) and when we apply wild bootstrap tests (see Appendix Table D8).

5.2 Evidence from the Delhi Primary Survey

We next utilize the sample from the Delhi Primary survey data to examine changes in monthly transportation expenditure, including bus expenses, at the *individual* level.[11] Among non-users, 64% spent ₹1∼1,000 per month on transportation and the remaining spent more than ₹1,000. Of users, both new and continuous, 55% did not spend any money on transportation, including buses, per month in the period after the program's launch. The remaining 45% spent between ₹1 and ₹1,000 on transportation. Specifically, among new bus users (see Figure 2), 82% spent more than ₹1,000 per month on transportation before the program, but this percentage decreased dramatically to 1% after the program was implemented. This 81% difference is also statistically significant at a 1% level. Furthermore, while none of the new bus users reported any spending on transportation before the program (the ₹0 category in Figure 2), the proportion increased to 53% after the program. To the extent that the two groups of users (new and continuous) are comparable, there is a notable shift in their travel expenditure patterns, which complements the household-level results presented above.

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

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 next.

6 Impact on Time Use

Our second set of main results pertains to time use. To reiterate, the CPHS reports daily time spent on work for employed women, household chores, and travel time, without breaking down the latter by motive for travel. Due to various substitution possibilities between travel modes, it is not clear whether total travel time will increase, decrease, or remain unchanged. It is possible that women switch from paid to free buses and there are no changes in travel time. However, if women who were previously budget-constrained switch from walking to taking free buses, travel time will be reduced. Yet a third possibility is that the price effect helps women who would have otherwise not gone out to take more buses, increasing their travel time. While our ability to shed direct light on mode substitution is limited by the CPHS data, empirical results could help discern the overall impact. Finally, reallocation from travel time may affect time spent on household chores, and the possibility of cheaper commutes may affect labor supply. In what follows, we first focus on employed women and document time use changes that vary by skill level and marriage status. Subsequently, we offer a simple model of intra-household time allocation, corroborating its implications by showing results for men's time use. Our final analysis documents results for unemployed women.

6.1 Time Use of Employed Women

We estimate equation (2) for employed women based on their current work status, and report the results in panel A of Table 3.[12] As shown in column 1, employed women in treated states spent less time traveling after the implementation of the free bus program

[12] While the baseline results do not consider the flows in and out of employment, in Appendix Table D9, we present a matrix of women's labor market status before and after the program. Among those employed in the post-treatment periods, 65.8% had also been employed before the program deployment. We thus also estimate equation (2) for women continuously employed during the study period to examine if the results are influenced by changes in employment status. The results are reported in Appendix Table D10. The estimated coefficients are similar to those in panel A of Table 3. In Appendix Table D11, we cluster the standard errors at the district level and the significance levels of the estimated coefficients are similar to those in panel A of Table 3 and Appendix Table D10.

compared to those in control states, which is consistent with a potential substitution from slower modes of travel (cheaper but slower buses or walking) to faster buses. These travel time savings can be allocated to household chores, additional work, or a combination. Surprisingly, we find that it is primarily the former: hours spent on domestic tasks increased by 19.1% (column 2), with minimal change in the time spent working (column 3).[13]

We then explore the potential heterogeneity of this pattern across employed women at various skill levels. We define low-skill women as individuals who have not received education beyond primary school, medium-skill women as those who have attended middle or secondary schools, and high-skill women as those who hold bachelor's degrees or above.[14] We document the results by skill levels in panel B of Table 3.[15] Although all women save time on travel, employed women across various skill levels allocate this saved time to different activities. Specifically, employed low-skill women reduce their work hours by 2 hours and increase their time spent on household activities by 1.1 hours, compared to high-skill women.[16] We see a similar pattern for medium-skill employed women, but the increase in time spent on household activities is 32 minutes less than their low-skill counterparts. Conversely, employed high-skill women increased their working time by 1.1 hours after the program compared to their counterparts in control states.

Next, we explore whether marital status plays any role in inducing women to spend

[13]The result in working hours may prompt inquiries about wage effect. We, therefore, also use the InP section data to examine the impact on employed women's wages and find a statistically insignificant increase in treated states compared to control states following the program's implementation, as shown in column 1 of Appendix Table D12. However, it should be noted the wage results presented in Appendix Table D12 are only suggestive evidence. We observe wages for 64% of the employed women featured in Table 3. Most of this attrition is not due to selection bias (i.e., respondents refusing to answer the income survey). Instead, when matching the PoI and the InP datasets, we find that over 70% of the unmatched observations result from interviewers being unable to reach the household within the available fixed period.

[14]Goel (2017) and Thomas (2011) classify skill levels by education levels. Asuyama (2012) categorizes "people who were illiterate or have only received education below the primary level" as individuals with the lowest skill level. Mehrotra, Gandhi and Sahoo (2013) also group people who have below primary or only primary level of education as individuals with low level of skill. In this paper, we follow previous literature and group skill level by education level, setting individuals who have not received education or have only attended primary school as low-skill individuals.

[15]These results are based on women's skill levels before the program's implementation. As shown in Appendix Table D13, only minor changes in skill status occurred from the pre- to the post-period. We further verify this point in a regression in columns 2 and 4 in Appendix Table D14.

[16]We also decompose the wage effect by skill levels. As shown in column 2 of Appendix Table D12, employed low-skill women in treated states experienced an imprecise decrease in wages compared to high-skill women relative to their counterparts in control states. The result is only suggestive, as noted in footnote 13.

more time on household chores despite reduced travel times following the implementation of the free bus program. In India, as in many other developing countries, social norms ascribe child rearing, grocery shopping, and cooking as roles to women. These gender-based expectations could impact married and unmarried employed women differently. We present the results on employed married women in Table 4. We find that employed married women saved 21.5% more time commuting than their unmarried counterparts.[17] However, they reallocated this saved time to household chores while reducing their time working.

Given the richness of our data, we then examine how the impacts on *employed married women* vary by skill level. The results are reported in Table 5, which are similar to the results in panel B of Table 3. The excluded category in the triple interaction specification is the high-skill employed married women. While the triple interactions show differential effects, we compute the overall effect for each skill category and report these at the bottom of the table, including the sum of the double and triple interaction coefficients and their p-values. In column (1), we observe that after the program's implementation, low-skill and medium-skill married women reduced their travel time by 21.0% and 21.7% compared to those in control states, respectively. Column (3) documents the effects on work time: compared to high-skill women, those with low skills substantially reduced their labor supply. The triple interaction estimate indicates a 40% relative decrease in labor supply. The overall effects for low and medium-skilled women are again reported at the bottom, showing an increase of 21.3% for low-skill and 9.9% for medium-skill. This saved time was redirected towards domestic tasks, resulting in a 37.1% and 27.3% increase for low- and medium-skill married women, respectively. Conversely, high-skill married women did not reallocate their time in this manner; instead, they utilized the saved travel time for work.

Our analysis suggests that the disproportionately large burden of household work on married women precludes them from fully benefiting in the labor market by searching for jobs or working more hours. Instead, these women use the time saved from commuting to assist their spouses and other men in the household, increasing their labor supply. Gender roles within households and bargaining power undermine the potential positive

[17] The current results are based on women's contemporary marital status but do not change if we use the pre-period status. As shown in Appendix Table D15, around 95% of women have the same status in the post-period as they do in the pre-period. In columns 1 and 3 of Appendix Table D14, we confirm that the program did not have any compositional effect on women's marital status. We also examine the impact on wages for employed married women and present the results in column 3 of Appendix Table D12. As expected, compared to employed unmarried women, there is a decline in wages for employed married women following the program's implementation. As noted previously in footnote 13, this piece of evidence is only suggestive.

effects of the program. In the following subsection, we provide a simple model of optimal time allocation within the household to formalize the mechanism and highlight the assumptions under which the model is consistent with the empirical findings. We also test the implication of the model for men's time spent on household chores.

6.2 A Model of Intra-Household Time Allocation

We build a model where household chores are reallocated from men to women among couples with low-skill women. These women reduce their labor supply. This could be driven by two possible channels operating in household-level decision-making aimed at maximizing joint utility. First, there may be a discrete shift from men to women in household chores that require a discrete amount of time. For example, a long commute by mothers may have previously made it optimal for the father to take their kids to school, perhaps on a bus. After the roll-out of free bus rides for women, this responsibility may be reallocated to the mother. The gender wage gap in India increases the likelihood of such re-optimization at the household level, as men typically earn more than women within the same household.[18]

A second mechanism could be the nature of work typically performed by women, which, compared to men, is less likely to be full-time with a fixed wage.[19] Let's discuss an illustrative example of a low-skill, part-time woman worker whose occupation is house cleaning. This woman commutes to a neighborhood with high socioeconomic status. Before the free rides program, she has a time-consuming commute on foot. This leads to an indivisible labor supply, where she finds it optimal to stay in the work neighborhood all day to clean multiple homes. However, when buses become free and the travel time between her residential and work neighborhoods decreases, she finds it optimal to skip cleaning one of the houses she previously cleaned. Instead, she takes a bus back to her neighborhood to run a household errand during the day, then returns to

[18]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. Note that 21% of the observations did not respond to the income survey, raising concerns about potential selection bias. However, over 70% of those who failed to report income did so because interviewers could not reach the households in time before the survey ended.

[19]Fletcher, Pande and Moore (2017) show that the types of jobs Indian women report vary by age but are primarily part-time, reflecting the demands of other household responsibilities, particularly in the context of marriage and childbearing. 73% of women willing to take a job prefer regular, part-time work, while only 22% report wanting regular, full-time work; the remaining 5% want a mixture of only occasional full or part-time work.

the work neighborhood for another job. This reallocation of time reduces her work and travel hours while increasing her time on household chores.

We now describe a simple model of optimal time allocation within the household to formalize this mechanism. Consider a different-sex household where the man engages in salaried work, such that his income, I_m, is independent of the hours worked. Conversely, the woman has a divisible labor supply at an hourly wage of w_f, where the subscript f denotes 'female'. The total female time endowment is E hours per day. There is an indispensable household chore requiring H hours. It is an indivisible activity, such as grocery shopping, which needs to be performed by either the man or the woman. The disutility of the chore is d_m and d_f for the man and woman, respectively.

The household maximizes joint utility by allocating the chore to one of its members, captured by an indicator function $\mathbb{1}_H$ that takes the value of one if it is performed by the woman, and zero otherwise:

$$\mathbb{1}_H = \begin{cases} 0 & \text{if household chore performed by the man,} \\ 1 & \text{if household chore performed by the woman.} \end{cases}$$

Note that in most households in India, both men and women share household work, with women typically performing the bulk of the tasks. For simplicity of exposition, we assume that either men or women perform household work, and the results hold even when household work is shared.

Household surplus is increasing in total income net of the disutility from the household chores. Total income depends on hours worked by the woman, which is the residual left after commuting C hours and taking care of H if she is responsible for the household chores:

$$\max_{\mathbb{1}_H = 0,1} \quad \underbrace{I_m - d_m(1 - \mathbb{1}_H)H}_{\text{man's surplus}} + \underbrace{w_f(E - C - \mathbb{1}_H \cdot H) - d_f \cdot \mathbb{1}_H \cdot H}_{\text{woman's surplus}}$$
$$\text{s.t.} \quad I_m + w_f(E - C - \mathbb{1}_H \cdot H) \geq \overline{w}$$

where the constraint captures the subsistence threshold of income $\overline{w}$ that the household needs to attain. We assume that male salary alone is not high enough to meet subsistence, i.e., $I_m < \overline{w}$, so that the woman needs to work regardless of C subject to the time constraint $E - C - \mathbb{1}_H \cdot H \geq 0$. We assume that the commute time $C \in \{C_{slow}, C_{fast}\}$ depends on whether the woman takes a slow or fast mode of transport, requiring a higher or lower travel time, $C_{slow} > C_{fast}$, respectively. Therefore, there is a trade-off in female time allocation between work versus commuting. Before the rollout of the program offering free bus rides to women, we assume that a slower and more time-consuming commute is chosen. We do not model a man's commute since his salary does not depend on the hours worked.

Next, we back out from the model the restrictions on the parameters needed for the optimal decisions to be compatible with our empirical results. If these restrictions are plausible, the model offers a useful lens through which these results can be interpreted. Recall that our objective is to rationalize the decrease in labor supply and the increase in household chores for women after the introduction of free bus rides. In our model, this corresponds to $\mathbb{1}_H = 0$ when $C = C_{slow}$, and $\mathbb{1}_H = 1$ when $C = C_{fast}$. Assuming that fast commuting by free buses leaves enough time for the woman to work even if she undertakes the household chore, i.e., $E - C_{fast} - H > 0$, the latter implies

$$I_m + w_f(E - C_{fast} - H) - d_f H \ > \ I_m - d_m H + w_f(E - C_{fast}) \quad \Rightarrow \quad d_m - d_f \ > \ w_f.$$

For these assumptions to be compatible with non-negative wages, gender-specific disutility of chores needs to satisfy $d_m > d_f$. Moreover, men's disutility has to be high enough so that hourly low-skill female wages cannot compensate for it within the household. This is a plausible assumption for a low-skill household in the Indian context.

However, without another restriction, $d_m - d_f > w_f$ would imply that household work would be allocated to the woman even before the program when $C = C_{slow}$. To rationalize $\mathbb{1}_H = 0$ when $C = C_{slow}$, it must be the case that doing both the household chores and working—which necessitates commuting—violates the time constraint of the woman: $E - C_{slow} - H < 0$. Hence, the two constraints faced by the household—to perform H and attain subsistence within the time endowment—leave no choice but for the man to do household chores and the woman to work. When commuting time drops, however, they find it optimal to reallocate the household work to the woman. For this to reduce her market work hours, model parameters have to satisfy

$$\underbrace{E - C_{slow}}_{\text{work hours before free buses}} \quad > \quad \underbrace{E - C_{fast} - H}_{\text{work hours after free buses}} \quad \Rightarrow \quad H \ > \ C_{slow} - C_{fast}.$$

That is, household chores are more time-consuming than the time saving from the free and faster commuting.

To sum up, three assumptions are sufficient to rationalize the estimated reallocation of chores within the household: a less lucrative labor force status for women (captured by the low hourly wage compared to the fixed male salary), 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).

Our model suggests that employed married men should increase their labor supply and reduce their time spent on household chores. We test this hypothesis using our data. The results are reported in Table 6. Consistently, we observe the opposite pattern for employed married men residing in households with employed women: they reduce their time devoted to household chores by 14.2%. This lends support to our model as the driving mechanism.

6.3 Impact on the Time Use for Unemployed Women

To complete our analysis, we shift our focus to examining unemployed women actively seeking jobs. First, we estimate equation (2) for these women, classifying them based on their current work status, and present the results in columns 1 and 2 of Table 7.[20] We find that unemployed women in treated states spend more time traveling and, concurrently, less time on domestic duties than their counterparts in control states following the implementation of the *Pink Slip* program. Such a shift implies a potential increase in the time these women allocate to job search.

We further investigate whether the changes are driven by the intensive margin or the extensive margin. To do so, we estimate equation (2) for women who have the same pre- and post-period labor market status–unemployed, and report the results in columns 3 and 4 of Table 7.[21] We find that the effects are more pronounced for unemployed women consistently unemployed over time, suggesting that these always-unemployed women are most responsive to the free bus tickets. Therefore, the changes are mainly driven by the intensive margin. Additionally, we estimate equation (1) for travel time for both currently unemployed women (Appendix Figure C3(a)) and always-unemployed women (Appendix Figure C3(b)). In both figures, unemployed women in treated states spent more time traveling after the program's implementation than those in the control states.

Similarly, we explore whether the time usage pattern for unemployed women holds

[20]In Appendix Table D16, we cluster the standard errors at the district level. Our results are qualitatively similar to those reported in Table 7.

[21]In Appendix Table D9, we present a matrix of women's labor market status before and after the program. Among those who were unemployed in the post-treatment periods, 58.3% were not employed in the pre-period.

across skill levels and whether married unemployed women also benefit. As shown in Appendix Table D17, the increase in travel time observed in column 1 of Table 7 is driven by high-skill unemployed women and unmarried unemployed women. Specifically, we observe a null effect (0.02 with $p > 0.10$) on travel time and an insignificant effect on time spent on household chores (-0.127 with $p > 0.10$) for married, unemployed women, suggesting the persistence of entrenched gender norms.

7 Impact on Employment and Job Search

Time spent on work is not applicable for unemployed women. However, they exhibit a travel time pattern similar to that of employed women: high-skilled unemployed women increase their travel time, while low-skilled women decrease it. This variation in travel time could plausibly involve job searches; thus, the *Pink Slip* program might impact women's labor market outcomes. Although we cannot directly measure travel time devoted to job searches in the CPHS data, we can infer its impact on labor market outcomes based on observed changes in participation, employment, or unemployment. We now present these results, followed by additional evidence on the purpose and distance of travel from the Delhi Primary Survey.

7.1 Evidence from the 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 columns 1 to 3 of Table 8. We find no statistically or economically significant impact on being in the labor market or being employed. However, there is a marginal increase in the job search for women. Women previously out of the labor market are 1.1% ($p < 0.15$) more likely to start searching for jobs after the program, which is 15.7% of the control mean. We also present the corresponding event study graph in Figure 3, which shows that this marginal increase persisted in the post-implementation periods. The estimated coefficients for periods 1 and 2 after the policy are statistically significant at 10% and 15% levels, respectively. In period 3, the magnitude remains unchanged, though it is imprecise. These findings suggest that more women are moving from being out of the labor market to actively looking for jobs, although they are not more likely to find employment in this short-run period.

7.2 Evidence from the Delhi Primary Survey

The Delhi Survey reports the purpose of travel and the average travel distance for each respondent.[22] We leverage this data to compare the purpose of travel and the average travel distance between new and continuous bus transit users in the post-implementation periods. 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). 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 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. We then restrict the matched sample to users whose travel purpose is work, which includes travel to work or job search depending on unreported employment status. 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. These results suggest that free passes enable women to travel greater distances, potentially allowing them to work in more remote jobs or facilitating their job search efforts.

8 Conclusion

In the face of extensive literature documenting that increased commuting costs often reduce women's work hours and labor force participation, there is growing policy attention towards reducing commuting barriers for women. Using the roll-out of free bus services for women in several states of India under the *Pink Slip* program, this paper

[22]While this data does not report employment status, the survey answer '*travel for work*' is meant to capture travel *to work* in the case of employed women and travel *to search for work* in the case of unemployed women.

evaluates the consequences of a reduction in commuting costs on women's time use, including work hours, travel times and time on household work, as well as their 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, implying that demand for bus transportation by women is elastic. We also show, however, that reducing commuting costs alone may not be enough for women to increase work hours or participate more in the labor market. Heterogeneous responses reflect the re-optimization of agents with varying demographic status: free buses incentivize unmarried, skilled, and unemployed women to increase labor force participation and search more intensively for jobs, respectively. Skilled and unmarried women who are already employed increase their work hours. However, low-skill and married women use the time saved from commuting and use free buses to do more household work, replacing some of the household work done by their spouses. These men increase their work hours. These results highlight the importance of household-level decision-making and intra-household bargaining power in determining gender norms that impede most vulnerable women from taking advantage of the free bus program to increase their labor supply.

Our findings have important policy implications: If the goal of providing free transportation to women is to improve women's labor market outcomes, only a tiny share of the workforce–primarily skilled unmarried women–benefits from this policy in the immediate short run.

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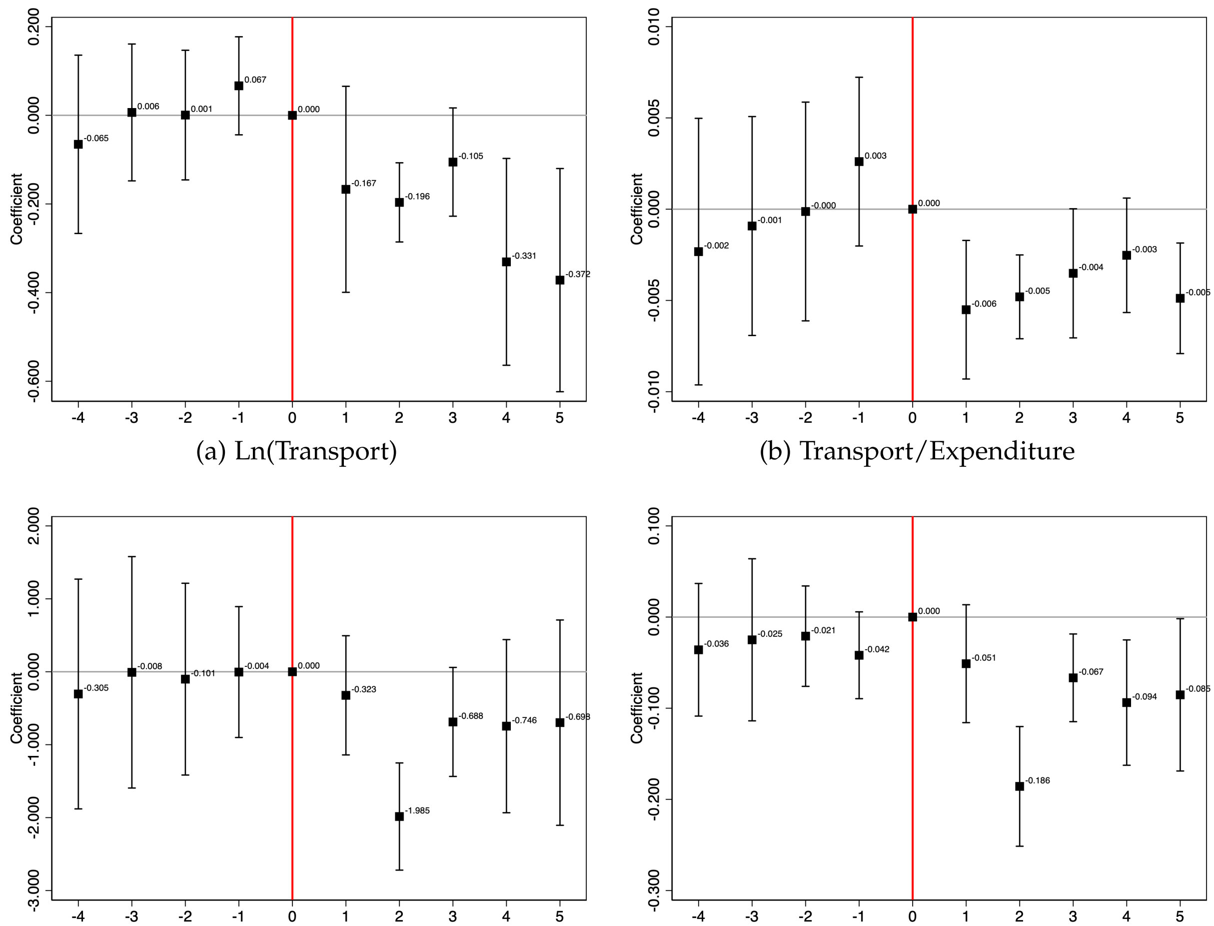
Figures



(a) Ln(Transport) (b) Transport/Expenditure

(c) Ln(BTF) (d) BTF/Transport

Figure 1: Event Study Graphs: Monthly Household Expenditure

<u>Notes:</u> "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 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, month, and year 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.

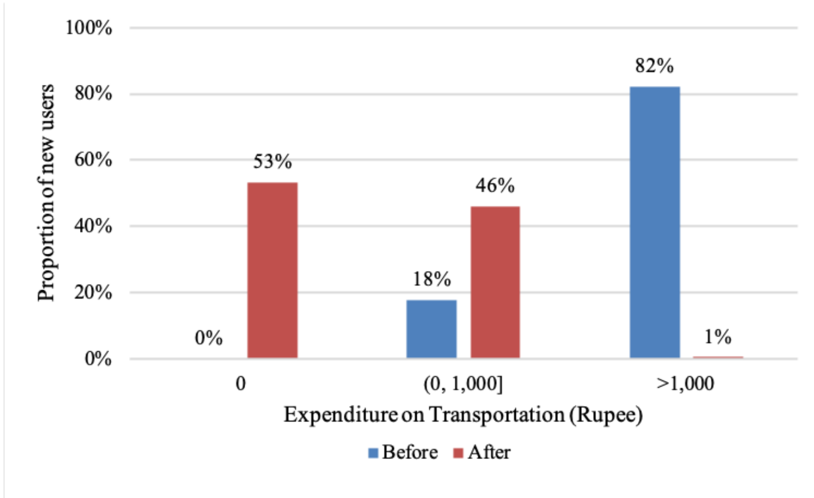


Figure 2: Monthly Expenditures (₹) on Transportation Before & After the Program

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 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.

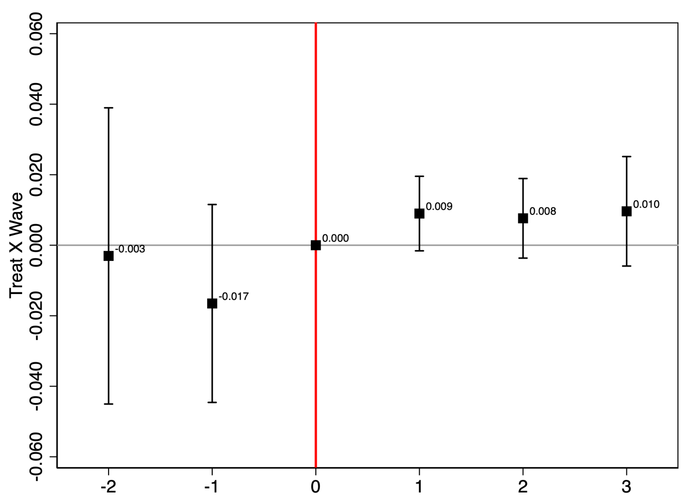


Figure 3: Event Study Graph: Job Search (Not Employed)

Notes: "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 January-April 2022 for both Punjab and Tamil Nadu. The regression includes individual, wave, and year-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. In the figure, the estimated coefficients in time periods 1 and 2 are statistically significant at 10% and 15% levels, respectively.

Tables

Table 1: User Perceptions of Buses & *Pink Slip* Scheme

	(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. * is p<0.1, ** is p<0.05, and *** is p<0.01.

Table 2: The Impact on Household Transportation Expenditures

	(1)	(2)	(3)	(4)	(5)
	Ln(Transport)	Ln(BTF)	Transport/Expenditure	BTF/Expenditure	BTF/Transport
Treat × Post	-0.197**	-0.801***	-0.004**	-0.003***	-0.066***
	(0.084)	(0.201)	(0.001)	(0.001)	(0.016)
HH FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Control Mean (Level)	349.97	100.56	0.03	0.01	0.28
R^2	0.62	0.68	0.67	0.64	0.62
No. of HHs	22,791	22,791	22,791	22,791	22,791
N	150,233	150,233	150,233	150,233	150,233

Notes: "Expenditure" = Total monthly household expenditure. "Transport" = Total monthly household expenditure on transport. "BTF" = Monthly household expenditure on daily bus/train/ferry fare. We conduct analysis on the sample of households who are also represented in the individual data. All regressions include individual, quarter/wave, and year-fixed effects and control for the average number of daily new confirmed cases as a share of the population. The control mean (level) in columns 1 and 2 are in Rupees. Standard errors are clustered at the state level. * is p<0.1, ** is p<0.05, and *** is p<0.01.

Table 3: The Impact on Time Use for Employed Women

	(1)	(2)	(3)
	Ln(Travel Time)	Ln(Time for HH)	Ln(Time for Work)
Panel A. Employed Women			
Treat × Post	-0.098***	0.191***	0.014
	(0.011)	(0.053)	(0.051)
Control Mean (Level)	0.60	3.01	6.72
R^2	0.52	0.53	0.43
Panel B. Employed Women By Skill			
Treat × Post	-0.076	-0.049	0.161*
	(0.070)	(0.060)	(0.085)
Treat × Post × Low-Skill	-0.065	0.377***	-0.292**
	(0.059)	(0.072)	(0.095)
Treat × Post × Medium-Skill	-0.002	0.199***	-0.100
	(0.076)	(0.040)	(0.084)
Control Mean (Level)	0.73	2.98	6.94
R^2	0.52	0.54	0.43
Individual FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
No. of Individuals	2,916	2,916	2,916
N	9,906	9,906	9,906

Notes: We restrict the sample to women who are employed. In this table, we categorize women by their current employment status. The omitted group is the employed high-skill 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-Skill" = Women who went to primary schools or received no education. "Medium-Skill" = Women who went to middle school, secondary schools, or higher secondary schools. All regressions include individual, quarter/wave, and year-fixed effects and control for the average number of daily new confirmed cases as a share of the population. The control mean (level) is hours per day and is the average for employed women in pre-periods and control states in panel A and is the average for employed high-skill women in control states during pre-periods in panel B. Standard errors are clustered at the state level. + is p<0.15, * is p<0.1, ** is p<0.05, and *** is p<0.01.

Table 4: The Impact on Time Use for Employed Women

	(1)	(2)	(3)
	Ln(Travel Time)	Ln(Time for HH)	Ln(Time for Work)
Treat × Post × Married	-0.215***	0.196**	-0.248***
	(0.026)	(0.059)	(0.061)
Individual FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Control Mean (Level)	0.70	2.69	7.21
R^2	0.52	0.54	0.43
No. of Individuals	2,916	2,916	2,916
N	9,906	9,906	9,906

Notes: We restrict the sample to employed women. In this table, we categorize individuals by their current employment status. 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, quarter/wave, and year-fixed effects and control for the average number of daily new confirmed cases as a share of the population. The control mean (level) is hours per day. The control mean is the average for employed unmarried women in control states during pre-periods. Standard errors are clustered at the state level. * is $p<0.1$, ** is $p<0.05$, and *** is $p<0.01$.

Table 5: The Impact on Time Use for Employed Married Women by Skill

	(1)	(2)	(3)
	Ln(Travel Time)	Ln(Time for HH)	Ln(Time for Work)
Treat × Post (TP)	-0.202*	0.021	0.185
	(0.103)	(0.098)	(0.153)
Treat × Post × Low-Skill (TPL)	-0.007	0.350***	-0.398*
	(0.093)	(0.099)	(0.176)
Treat × Post × Medium-Skill (TPM)	-0.014	0.252***	-0.284^{+}
	(0.119)	(0.059)	(0.177)
TP+TPL	-0.210***	0.371***	-0.213**
p-value	(0.000)	(0.000)	(0.048)
TP+TPM	-0.217***	0.273***	-0.099**
p-value	(0.000)	(0.002)	(0.047)
Individual FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Control Mean (Level)	0.62	3.48	6.68
R^2	0.53	0.54	0.43
No. of Individuals	1,602	1,602	1,602
N	5,038	5,038	5,038

Notes: We restrict the sample to employed married women. The omitted group is the high-skill women who have bachelor's degrees or above. "Low-Skill" = Women who went to primary schools or received no education. "Medium-Skill" = 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, quarter/wave, and year-fixed effects and control for the average number of daily new confirmed cases as a share of the population. The control mean (level) is hours per day. The control mean is the average for employed high-skill married women in pre-periods and control states. Standard errors are clustered at the state level. * is $p<0.1$, ** is $p<0.05$, and *** is $p<0.01$.

Table 6: The Impact on Time Use for Employed Men

	(1)	(2)
	Ln(Travel Time)	Ln(Time for HH)
Treat × Post × Married	-0.010	-0.142**
	(0.037)	(0.054)
Individual FE	Yes	Yes
Wave FE	Yes	Yes
Year FE	Yes	Yes
Control Mean (Level)	0.79	1.51
R^2	0.52	0.71
No. of Individuals	1,867	1,867
N	7,318	7,318

Notes: We restrict the sample to employed men from *households* with employed women (the sample in Table 4). In this table, we categorize individuals by their current employment status. A man is unmarried if he is divorced, unmarried, or widowed. The omitted group is employed unmarried men. "Travel Time" = Time spent on travel. "Time for HH" = Time spent on household activities. "Married" = A dummy takes the value of one if a man is married and zero if the man is divorced, unmarried, or widowed. All regressions include individual, quarter/wave, and year-fixed effects and control for the average number of daily new confirmed cases as a share of the population. The control mean (level) is hours per day. The control mean is the average for employed unmarried men in control states during preperiods. Standard errors are clustered at the state level. * is p<0.1, ** is p<0.05, and *** is p<0.01.

Table 7: The Impact on Time Use for Unemployed Women

	(1)	(2)	(3)	(4)
	Unemployed Women		Always Unemployed Women	
	Ln(Travel Time)	Ln(Time for HH)	Ln(Travel Time)	Ln(Time for HH)
Treat × Post	0.102^{+}	-0.437^{+}	0.144***	-0.596**
	(0.056)	(0.249)	(0.042)	(0.236)
Individual FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control Mean (Level)	0.24	2.58	0.27	1.82
R^2	0.64	0.75	0.99	0.73
No. of Individuals	1,570	1,570	776	776
N	5,636	5,636	3,197	3,197

Notes: We restrict the sample to women who are unemployed but actively seeking employment. In columns 1-2, we categorize women by their current employment status; and in columns 3-4, the employment status of women remains constant over time. "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, quarter/wave, and year-fixed effects and control for the average number of daily new confirmed cases as a share of the population. The control mean (level) is hours per day and is the average for women in pre-periods and control states. Standard errors are clustered at the state level. + is p<0.15, * is p<0.1, ** is p<0.05, and *** is p<0.01.

Table 8: The Impact on Labor Market Status for Women

	(1)	(2)	(3)
	in Labor Mkt.	Employed	Job Search (Not Employed)
Treat × Post	0.003	-0.017	0.011^{+}
	(0.011)	(0.016)	(0.006)
Control Mean (Level)	0.14	0.51	0.07
R^2	0.81	0.89	0.78
No. of Individuals	43,855	4,537	41,347
N	189,668	16,007	177,657
Individual FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

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. "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. "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. All regressions include individual, quarter/wave, and year-fixed effects and control for the average number of daily new confirmed cases as a share of the population. The control mean (level) is the proportion of women belonging to a specific status in pre-periods and control states. Standard errors are clustered at the state level. + is p<0.15, * 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. * is p<0.1, ** is p<0.05, and *** is p<0.01.

APPENDIX

A Data

A.1 Construction of a State Panel for Synthetic Difference-in-Difference

States that implemented the *Pink Slip* program could exhibit dissimilarities from other states, including neighboring ones. To mitigate this concern, we utilize a synthetic difference-in-differences approach (SDID) proposed by Arkhangelsky et al. (2021). The SDID method re-weights 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 establishes a synthetic counterfactual state for causal estimation. Since our treatment occurs at the state level rather than the household (or individual) level, we aggregate our household-level (or individual) data to the state level and then match states and their pre-trends using a set of variables discussed below

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 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 nine 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 use the average new confirmed daily cases as a share of the state population.

Using this approach, we compare the outcomes of treated states with that of a weighted combination of control states, the "synthetic" treated states without the free bus ride program, which has similar pre-treatment trends as the treated group. The weights applied in our regression for the household-level analysis and individual-level analysis are defined as follows:

$$\text{Household-Level:} \qquad \text{Weight}_{ijt} = \text{State Weight}_j \times \text{Time}_t \times \text{Household Weight}_{it}, \tag{4}$$

$$\text{Individual-Level:} \qquad \text{Weight}_{ijt} = \text{State Weight}_j \times \text{Time}_t \times \text{Individual Weight}_{it}. \tag{5}$$

In equations (4) and (5), "State Weight$_j$" and "Time$_t$" are the state unit weights and time weights derived from SDID, respectively. "Household Weight$_{it}$" is the sampling weight of a household in the CPHS data. "Individual Weight$_{it}$" is the sampling weight of a member of a sample household in the CPHS data.

A.2 Delhi Primary Survey

Travel Purpose & Distance The survey inquires about respondents' primary travel purpose during the post-program period, offering a selection of options including work (including work and job search), education, healthcare, shopping, religion, leisure, pick/drop off, and others. Additionally, the survey collects information regarding users' average travel distances and average travel distances specifically by buses. It should be noted that the survey only asked new users but not continuous users about their average travel distance prior to the implementation of the program.

B Additional Figures

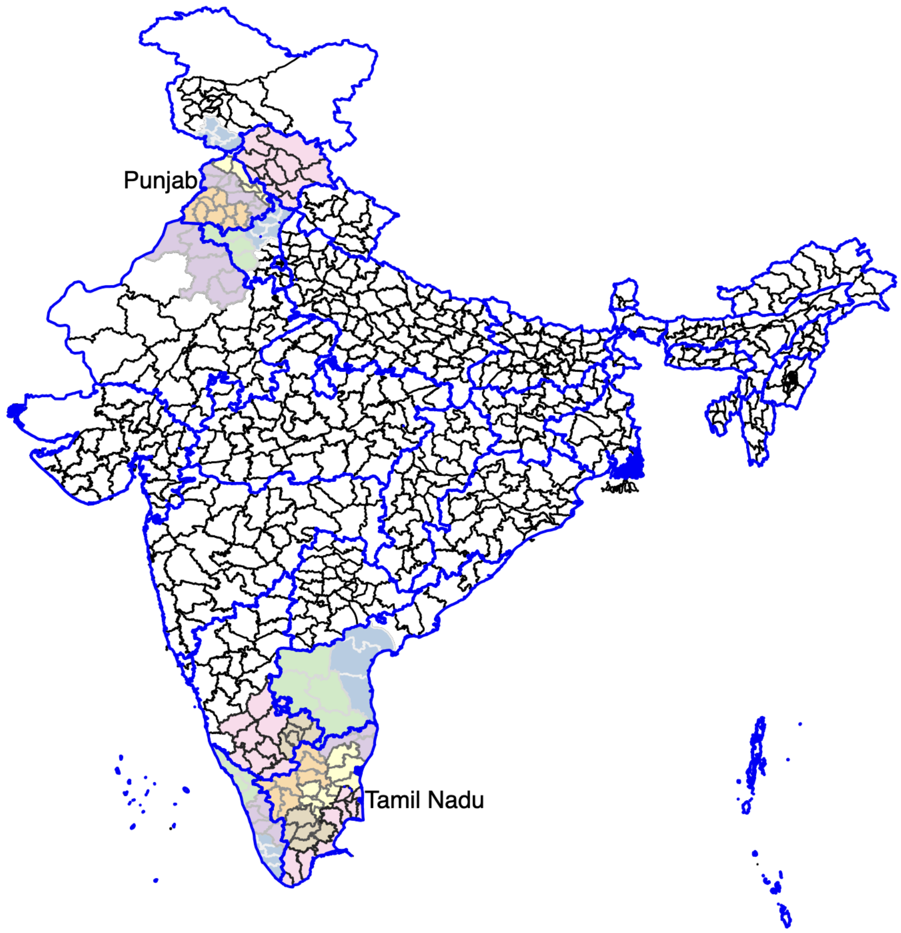


Figure C1: Map of Treated and Control Regions

Notes: Blue and black lines demarcate states and districts, respectively. Each homogeneous region (HR) is demarcated by a group of districts within a state sharing the same color. The two treated states of Punjab and Tamil Nadu are labeled. They have 3 and 5 HRs, respectively. Control regions are the neighboring HRs across state boundaries.

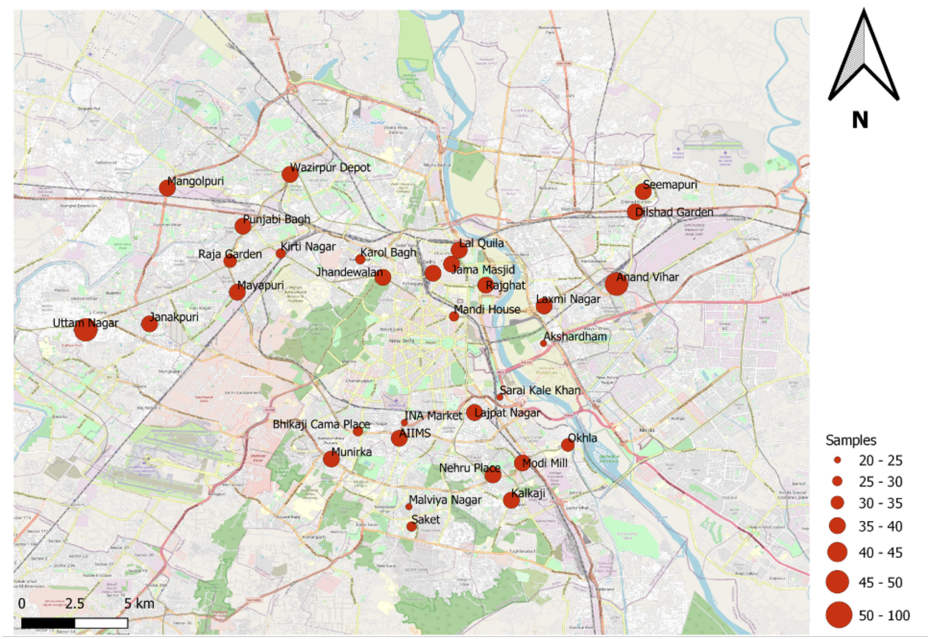
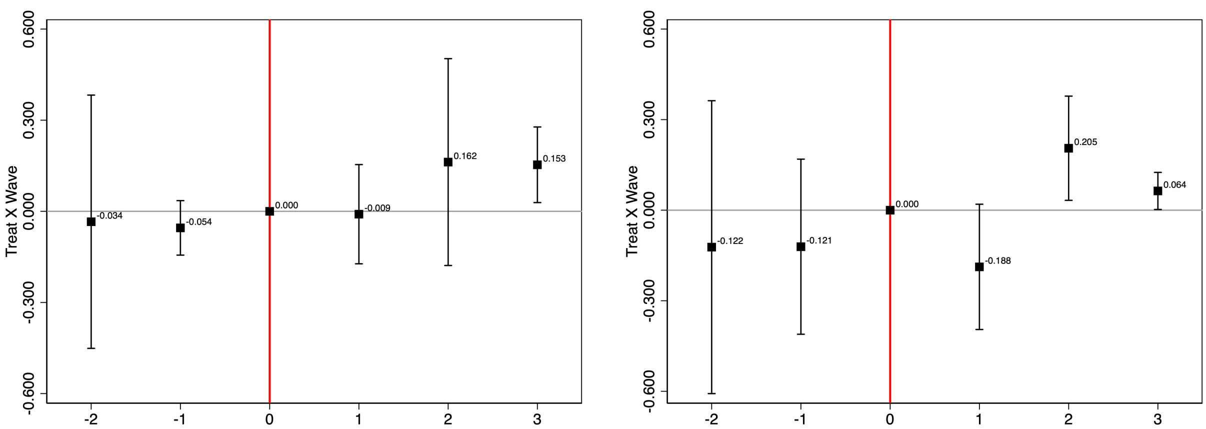


Figure C2: Map of Delhi Sample Locations

<u>Notes:</u> 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.



(a) Ln(Travel Time), Currently Unemployed Women (b) Ln(Travel Time), Always Unemployed Women

Figure C3: Event Study Graphs: Time Spent on Travel

<u>Notes:</u> "Travel Time" = Average daily time spent on travel. 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 January-April 2022 for both Punjab and Tamil Nadu. All regressions include individual, wave, and year 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.

C Additional Tables

Table D1: Treated vs. Control States

Group	Treated State	Control States
Group A	Punjab	Rajasthan, Haryana, Jammu & Kashmir, Himachal Pradesh
Group B	Tamil Nadu	Kerala, Karnataka, Andhra Pradesh

Table D2: Definition of Time Periods in CP, InP & PoI

Panel A. Consumption Pyramids (CP) & Income Pyramids (InP)				
	$Time_t$	Group A	Group B	$Post_t$
	-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	$Time_t$	Group A	Group B	$Post_t$
20	-2	May-Aug 2020	May-Aug 2020	0
21	-1	Sept-Dec 2020	Sept-Dec 2020	0
22	0	Jan-Apr 2021	Jan-Apr 2021	0
23	1	**May-Aug 2021**	**May-Aug 2021**	1
24	2	Sept-Dec 2021	Sept-Dec 2021	1
25	3	Jan-Apr 2022	Jan-Apr 2022	1

Notes: The time unit in the CP and InP data is a month, while in the PoI data, it is a wave. The boxed red time period is when the event (*Pink Slip* program) starts.

Table D3: 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.
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 work done for the employer. The forms of employment include self-employment and salaried jobs.
Travel Time	Average daily time spent on 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 a woman 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	A dummy variable is equal to one if a woman is employed and zero if a woman is in the labor market but unemployed. This variable is defined separately for the pre and post periods.
Job Search (Not Employed)	A dummy variable is equal to one if she is unemployed and is looking for a job and zero if a woman is out of the labor market. This variable is defined separately for the pre and post periods.
Out of Labor Mkt. $\rightarrow$ Employed	A sub-sample (360) of women who are out of the labor market in the pre-period and become employed in at least one post-period wave.
Out of Labor Mkt. $\rightarrow$ Unemployed	A sub-sample (405) of women who are out of the labor market in the pre-period and start searching for a job in at least one post-period wave. It should be noted that the sub-samples of "Out of Labor Mkt. $\rightarrow$ Employed" and "Out of Labor Mkt. $\rightarrow$ Unemployed" are mutually exclusive. We excluded 29 women who experienced both employment and unemployment in the post-period.
Education	
Middle	A dummy variable equal to one if a woman has gone to a middle school and zero otherwise.
High	A dummy variable equal to one if a woman has gone to a secondary school or a higher secondary school and zero otherwise.
$\geq$Bachelor	A dummy variable is equal to one if a woman has at least a bachelor's degree and zero otherwise.

Table D3 continued from previous page

Variable Name	Definition
Skill	
Low-Skill	A dummy variable equal to one if a woman has gone to primary schools or received no education and zero otherwise.
Medium-Skill	A dummy variable equal to one if a woman has gone to a middle school, a secondary school, or a higher secondary school and zero otherwise.
Skilled	A dummy variable is equal to one if a woman has at least a bachelor's degree and zero otherwise.
Marital status	
Married	A dummy variable is equal to one if a woman is married and zero if a woman is divorced, unmarried, or widowed.

Table D4: 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	9,380	0.259	5,992	0.246	0.013*
		(0.438)		(0.431)	(0.007)
Number of household members					
1∼3	9,380	0.483	5,992	0.595	-0.112***
		(0.500)		(0.491)	(0.008)
4∼6	9,380	0.179	5,992	0.120	0.060***
		(0.384)		(0.325)	(0.006)
≥7	9,380	0.338	5,992	0.285	0.053***
		(0.473)		(0.451)	(0.008)
Annual income of households					
≤₹200,000	9,380	0.346	5,992	0.557	-0.211***
		(0.476)		(0.497)	(0.008)
200,000∼₹400,000	9,380	0.474	5,992	0.299	0.175***
		(0.499)		(0.458)	(0.008)
≥₹400,000	9,380	0.180	5,992	0.144	0.036***
		(0.384)		(0.351)	(0.006)
Monthly household expenditure					
Expenditure	9,380	14,356.035	5,992	13,120.722	1,235.312***
		(6,903.750)		(5,669.422)	(106.682)

Table D4 continued from previous page

	(1) Control		(2) Treated		t-test Difference
Variable	N	Mean/SD	N	Mean/SD	(1)-(2)/SE
Transport	9,380	348.090	5,992	382.163	-34.073***
		(262.673)		(292.496)	(4.542)
BTF	9,380	107.191	5,992	110.559	-3.368*
		(115.407)		(111.090)	(1.881)
Panel B. Individual, May-August 2020					
Age	11,958	42.927	8,394	43.317	-0.390*
		(14.255)		(14.309)	(0.203)
Married	11,958	0.751	8,394	0.736	0.015**
		(0.432)		(0.441)	(0.006)
Education					
Primary School	11,958	0.217	8,394	0.233	-0.015***
		(0.412)		(0.422)	(0.006)
Middle School	11,958	0.174	8,394	0.225	-0.051***
		(0.379)		(0.418)	(0.006)
Secondary & Higher Secondary School	11,958	0.451	8,394	0.403	0.047***
		(0.498)		(0.491)	(0.007)
$\geq$ Undergraduate	11,958	0.113	8,394	0.131	-0.018***
		(0.317)		(0.338)	(0.005)
Labor market participation					
in Labor Mkt.	11,958	0.145	8,394	0.087	0.057***
		(0.352)		(0.283)	(0.005)
Employed	1,732	0.515	734	0.678	-0.163***
		(0.500)		(0.467)	(0.022)
Time usage					
Time for HH	11,958	4.930	8,394	6.491	-1.560***
		(3.044)		(2.721)	(0.042)
Travel Time	11,958	0.198	8,394	0.107	0.091***
		(0.382)		(0.258)	(0.139)
Time for Work	892	6.119	498	7.058	-0.939***
		(2.602)		(2.249)	(0.005)

<u>Notes:</u> "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. * is $p<0.1$, ** is $p<0.05$, and *** is $p<0.01$.

Table D5: Summary Statistics: Delhi Primary Survey (Individual Level)

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

Table D5 continued from previous page

Variable	(1) Non-users N	Mean/SD	(2) Users N	Mean/SD	t-test Difference (1)-(2)/SE
Religious	500	0.018	1,525	0.129	-0.111***
		(0.133)		(0.336)	
Shopping	500	0.034	1,525	0.065	-0.031***
		(0.181)		(0.246)	
Work	500	0.806	1,525	0.365	0.441***
		(0.396)		(0.481)	

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. * is p<0.1, ** is p<0.05, and *** is p<0.01.

Table D6: The Impact on Household Transportation Expenditures: Robustness to Policy Controls

	(1) Ln(Transport)	(2) Ln(BTF)	(3) Transport/Expenditure	(4) BTF/Expenditure	(5) BTF/Transport
Treat × Post	-0.258**	-0.883**	-0.003*	-0.003***	-0.068***
	(0.081)	(0.342)	(0.002)	(0.001)	(0.017)
Control Mean (Level)	349.97	100.56	0.03	0.01	0.28
R^2	0.63	0.68	0.67	0.64	0.62
No. of HHs	22,791	22,791	22,791	22,791	22,791
N	150,233	150,233	150,233	150,233	150,233
HH FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

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. "Expenditure" = Total monthly household expenditure. "Transport" = Total monthly household expenditure on transport. "BTF" = Monthly household expenditure on daily bus/train/ferry fare. We conduct analysis on the sample of households who are also represented in the individual data. All regressions include individual, quarter/wave, and year-fixed effects and control for the average number of daily new confirmed cases as a share of the population. The control mean (level) in columns 1 and 2 are in Rupees. Standard errors are clustered at the state level. * is p<0.1, ** is p<0.05, and *** is p<0.01.

Table D7: The Impact on Household Transportation Expenditures: Standard Error Clustered at the District Level

	(1) Ln(Transport)	(2) Ln(BTF)	(3) Transport/Expenditure	(4) BTF/Expenditure	(5) BTF/Transport
Treat × Post	-0.197**	-0.801***	-0.004***	-0.003***	-0.066**
	(0.079)	(0.227)	(0.001)	(0.001)	(0.029)
Control Mean (Level)	349.97	100.56	0.03	0.01	0.28
R^2	0.62	0.68	0.67	0.64	0.62
No. of HHs	22,791	22,791	22,791	22,791	22,791
N	150,233	150,233	150,233	150,233	150,233
HH FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes

Notes: This table replicates Table 2 in the main text by clustering standard errors at the district level. "Expenditure" = Total monthly household expenditure. "Transport" = Total monthly household expenditure on transport. "BTF" = Monthly household expenditure on daily bus/train/ferry fare. We conduct analysis on the sample of households who are also represented in the individual data. All regressions include individual, quarter/wave, and year-fixed effects and control for the average number of daily new confirmed cases as a share of the population. The control mean (level) in columns 1 and 2 are in Rupees. Standard errors are clustered at the district level. * is p<0.1, ** is p<0.05, and *** is p<0.01.

Table D8: The Impact on Household Transportation Expenditures: Wild Bootstrapped Standard Error

	(1)	(2)	(3)	(4)	(5)
	Ln(Transport)	Ln(BTF)	Transport/Expenditure	BTF/Expenditure	BTF/Transport
Treat × Post	-0.197**	-0.801*	-0.004^{+}	-0.003**	-0.066*
	(0.012)	(0.074)	(0.105)	(0.012)	(0.082)
HH FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Control Mean (Level)	349.97	100.56	0.03	0.01	0.28
R^2	0.62	0.68	0.67	0.64	0.62
No. of HHs	22,791	22,791	22,791	22,791	22,791
N	150,233	150,233	150,233	150,233	150,233

Notes: "Expenditure" = Total monthly household expenditure. "Transport" = Total monthly household expenditure on transport. "BTF" = Monthly household expenditure on daily bus/train/ferry fare. We conduct analysis on the sample of households who are also represented in the individual data. All regressions include individual, quarter/wave, and year-fixed effects and control for the average number of daily new confirmed cases as a share of the population. The control mean (level) in columns 1 and 2 are in Rupees. We report the wild bootstrap standard errors in parentheses. + is p<0.15, * is p<0.1, ** is p<0.05, and *** is p<0.01.

Table D9: Share of Women by Labor Market Status

		Post-periods			
		Out	Employed	Unemployed	Any
Pre-periods	Out	88.7%	**6.2%**	**10.0%**	57.1%
	Employed	0.6%	**65.8%**	1.3%	10.4%
	Unemployed	0.5%	1.4%	**58.3%**	8.2%
	Any	10.2%	26.6%	30.4%	24.3%
	Total	100%	100%	100%	100%

Notes: "Out" = Out of the labor market. "Any" = The women experienced more than one labor market status during pre- or post-periods.

Table D10: The Impact on Time Use for Always Employed Women

	(1) Ln(Travel Time)	(2) Ln(Time for HH)	(3) Ln(Time for Work)
Treat × Post	-0.117***	0.145***	0.025
	(0.012)	(0.025)	(0.035)
Individual FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Control Mean (Level)	0.63	3.04	6.86
R^2	0.58	0.60	0.38
No. of Individuals	1,687	1,687	1,687
N	6,408	6,408	6,408

Notes: We restrict the sample to employed women. In this table, the employment status of women remains constant over time. "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, quarter/wave, and year-fixed effects and control for the average number of daily new confirmed cases as a share of the population. The control mean (level) is hours per day and is the average for women in pre-periods and control states. Standard errors are clustered at the state level. + is p<0.15, * is p<0.1, ** is p<0.05, and *** is p<0.01.

Table D11: The Impact on Time Use for Employed Women (SE at the District Level)

	(1)	(2)	(3)
Panel A. By Current Employment Status			
	Employed Women		
	Ln(Travel Time)	Ln(Time for HH)	Ln(Time for Work)
Treat × Post	-0.098**	0.191***	0.014
	(0.048)	(0.062)	(0.070)
Control Mean (Level)	0.60	3.01	6.72
R^2	0.52	0.53	0.43
No. of Individuals	2,916	2,916	2,916
N	9,906	9,906	9,906
Panel B. By Always-Employment Status (Same Employment Status Over Time)			
	Always-Employed Women		
	Ln(Travel Time)	Ln(Time for HH)	Ln(Time for Work)
Treat × Post	-0.117*	0.145***	0.025
	(0.059)	(0.050)	(0.062)
Control Mean (Level)	0.63	3.04	6.86
R^2	0.58	0.60	0.38
No. of Individuals	1,687	1,687	1,687
N	6,408	6,408	6,408
Individual FE	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes

Notes: We restrict the sample to employed women. In Panel A, we categorize women based on their current employment status. In Panel B, we include only those women who are employed in both the pre- and post-periods. "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, quarter/wave, and year-fixed effects and control for the average number of daily new confirmed cases as a share of the population. The control mean (level) in columns 1-3 are hours per day and is the average for women in pre-periods and control states. Standard errors are clustered at the district level. * is p<0.1, ** is p<0.05, and *** is p<0.01.

Table D12: Impacts on Wages for Employed Women

	(1)	(2)	(3)
Treat × Post	0.120	0.119	0.299
	(0.239)	(0.137)	(0.263)
Treat × Post × Married			-0.464**
			(0.153)
Treat × Post × Low-skill (TPL)		-0.354	
		(0.354)	
Treat × Post × Medium-skill (TPM)		0.208	
		(0.170)	
Individual FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Control Mean (Level)	2049.36	3636.46	3757.70
R^2	0.86	0.86	0.86
No. of Individuals	1,866	1,866	1,866
N	9,143	9,143	9,143

Notes: The outcome variable is the log of monthly wages. We restrict the sample to employed women. The Income Pyramids (InP) data is collected on a monthly basis at the individual level. To ensure consistency with our Consumption Pyramids (CP) data, we use the same sample period as in CP (November 2020 to September 2021), which is displayed in Table D2. All regressions include individual, quarter/wave, and year-fixed effects and control for the average number of daily new confirmed cases as a share of the population. The control mean (level) represents the average monthly wages (₹) across various categories: employed women in control states during pre-periods (column 1), employed high-skill women in control states during pre-periods (column 2), and employed unmarried women in control states during pre-periods (column 3). Standard errors are clustered at the state level. * is p<0.1, ** is p<0.05, and *** is p<0.01.

Table D13: Share of Women by Skill

		Post-periods			
		Low-skill	Medium-skill	Skilled	Total
Pre-periods	Low-skill	99.3%	0.7%	0.0%	100%
	Medium-skill	0.0%	100.0%	0.0%	100%
	Skilled	0.0%	0.0%	100.0%	100%

Notes: The table presents the proportion of women who belong to a specific skill group and continue to be part of the same group in the post-periods. For example, around 99% of women who were classified as low-skill during the pre-periods maintained their low-skill status in the post-periods.

Table D14: The Impact on Women's Marital Status and Skills

	(1)	(2)	(3)	(4)
	All Women		Employed Women	
	Married	Skill	Married	Skill
Treat × Post	0.005	0.002	0.006	-0.002
	(0.006)	(0.005)	(0.008)	(0.006)
Control Mean	0.75	0.86	0.60	0.90
R^2	0.93	0.93	0.90	0.98
No. of Individuals	43,855	43,855	2,916	2,916
N	189,668	189,668	9,906	9,906
Individual FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes

Notes: "Married" = A dummy takes the value of one if a woman is married and zero if the woman is divorced, unmarried, or widowed. "Skill" = A categorical variable assigns 0 to women classified as low-skill, 1 to those classified as medium-skill, and 2 to those classified as skilled. All regressions include individual, quarter/wave, and year-fixed effects. The control mean is the average of the outcome variable for women in pre-periods and control states. Standard errors are clustered at the state level. * is p<0.1, ** is p<0.05, and *** is p<0.01.

Table D15: Share of Women by Marital Status

		Post-periods		
		Unmarried	Married	Total
Pre-periods	Unmarried	94.5%	5.5%	100%
	Married	3.2%	96.8%	100%

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 D16: The Impact on Time Use for Unemployed Women (SE at the District Level)

	(1)	(2)	(3)	(4)
	Unemployed Women		Always Unemployed Women	
	Ln(Travel Time)	Ln(Time for HH)	Ln(Travel Time)	Ln(Time for HH)
Treat × Post	0.102*	-0.437***	0.144	-0.596***
	(0.058)	(0.140)	(0.114)	(0.236)
Individual FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control Mean (Level)	0.24	2.58	0.27	1.82
R^2	0.64	0.75	0.99	0.73
No. of Individuals	1,570	1,570	776	776
N	5,636	5,636	3,197	3,197

Notes: We restrict the sample to unemployed women who are actively seeking employment. In Panel A, we categorize women based on their current employment status. In Panel B, we include only those women who are unemployed in both the pre- and post-periods. "Time for HH" = Time spent on household activities. "Travel Time" = Time spent on travel. All regressions include individual, quarter/wave, and year-fixed effects and control for the average number of daily new confirmed cases as a share of the population. The control mean (level) in columns 1-4 are hours per day and is the average for women in pre-periods and control states. Standard errors are clustered at the district level. * is p<0.1, ** is p<0.05, and *** is p<0.01.

Table D17: The Impact on Time Use for Unemployed Women by Skill and by Marital Status

	By Skill		By Marital Status	
	(1)	(2)	(3)	(4)
	Ln(Travel Time)	Ln(Time for HH)	Ln(Travel Time)	Ln(Time for HH)
Treat × Post	0.157**	-0.465**	0.093+	-0.493+
	(0.061)	(0.185)	(0.054)	(0.297)
Treat × Post × Low-skill	-0.148	0.217		
	(0.149)	(0.173)		
Treat × Post × Medium-skill	-0.135+	0.287**		
	(0.082)	(0.108)		
Treat × Post × Married			-0.095*	0.366+
			(0.049)	(0.201)
Individual FE	Yes	Yes	Yes	Yes
Wave FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Control Mean	0.25	3.05	0.18	3.89
R^2	0.64	0.75	0.64	0.75
No. of Individuals	1,570	1,570	1,570	1,570
N	5,636	5,636	5,636	5,636

Notes: We restrict the sample to women who are unemployed but actively seeking employment. In this table, we categorize women by their current employment status. "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, quarter/wave, and year-fixed effects and control for the average number of daily new confirmed cases as a share of the population. The control mean (level) is hours per day. It is the average for unemployed skilled women in pre-periods and control states in columns 1-2 and is the average for unemployed unmarried women in pre-periods and control states in columns 3-4. Standard errors are clustered at the state level. + is p<0.15, * is p<0.1, ** is p<0.05, and *** is p<0.01.