Labour Market Impacts of Free Bus Travel For Women: Evidence from Time Use Data

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Abstract

This paper examines how India's recent fare-free public bus schemes for women have influenced women's employment, mobility, and time allocation across five states—Delhi, Punjab, Tamil Nadu, Karnataka and Telangana. Using the two rounds of the nationally representative Time Use Survey (TUS) and exploiting temporal and spatial variation in policy rollout, We estimate Difference-in-Differences and triple-difference models comparing women and men in treated and untreated states before and after implementation. The TUS provides detailed, diary-based measures of labour supply, commuting, unpaid domestic work, and time spent outside the home, enabling a multidimensional assessment of mobility constraints. Across states, the estimates show modest but meaningful increases in certain forms of women's labour supply, particularly in outside-home employment minutes and, in some cases, informal or regular wage work. Effects on total travel are small, indicating that fare elimination primarily relaxes specific participation constraints rather than substantially expanding overall mobility. Domestic work adjustments are limited and heterogeneous. Overall, the results point to incremental but non-uniform shifts in women's economic engagement consistent with reductions in travel-cost and mobility frictions. Robustness checks, including placebo dates and border-district comparison designs, support the credibility of the findings. By combining state policy variation with rich time-use data, the paper provides the first multi-state evidence on the behavioural impacts of gender-targeted transport subsidies in India

and highlights both the promise and limits of mobility-oriented interventions for easing women's labour supply constraints.

Keywords: Gender, Labor Supply, Time Use, Transport Policy, Difference-in-Differences

JEL Codes: J16, J22, R41, O18

1 Introduction

Women in India face some of the lowest labour-force participation rates in the world, despite rapid economic growth and demographic transformation. A substantial body of research links these patterns to severe mobility constraints, safety concerns, time burdens from unpaid domestic work, and the high relative cost of travel for women. As a consequence, mobility restrictions and gender-specific transport costs form a central pathway through which women's access to labour markets and public spaces is curtailed. State governments in India have recently responded to these barriers by introducing free or subsidised public bus travel for women. Beginning with Delhi's "Pink Pass" in late 2019, similar programs have since been adopted in Punjab (2021), Tamil Nadu (2021), Karnataka (2023), and Telangana (2023), collectively covering millions of women with the explicit aim of improving labour-market access and economic security. Despite the prominence of these schemes, systematic evidence on their impacts remains scarce. Existing studies of transport subsidies or fare reductions focus largely on single settings, rely on administrative ridership data rather than behavioural measures, or evaluate changes in mobility without directly linking them to labour supply. Moreover, India's context differs sharply from settings where fare-free transit has been studied, due to the scale of gender gaps in employment, the burden of unpaid household responsibilities borne by women, and the prevalence of informal and home-based work. Understanding how women adjust their time allocation—not only whether they travel more—is essential for evaluating whether such schemes relieve binding constraints. This paper provides the first multi-state evaluation of India's fare-free bus policies for women using nationally representative time-use data. The analysis exploits variation in policy rollout across states and

across survey years in the 2019 and 2024 Time Use Surveys. The diary-based structure of the TUS enables construction of finely disaggregated measures of employment minutes, outside-home work, informal self-employment, regular wage work, commuting for employment, total travel across all purposes, domestic chores, and work-from-home. These measures allow an assessment that goes beyond conventional binary labour-force outcomes to capture the channels through which reduced travel costs may influence women's daily behaviour. The results are modest but informative. Across states, We find small increases in women's employment minutes, particularly in outside-home forms of work, but limited changes in total travel. These patterns suggest that fare elimination may allow some women to reallocate time toward paid work without proportionately expanding overall mobility. Effects vary across states, consistent with differences in baseline labour-force participation, policy design, and enforcement. Changes in unpaid domestic work are small and inconsistent, reflecting persistent time burdens that mobility interventions alone may not substantially relax. While estimates are not uniform across specifications, the overall direction of results is consistent with the easing of some—but not all—mobility-related barriers. By integrating administrative policy timing with detailed behavioural data, this paper contributes new evidence on the role of gender-targeted transport subsidies in shaping women's economic participation. The findings underscore both the potential for mobility interventions to relax participation constraints and the limits imposed by broader structural and social barriers that continue to shape women's time use.

2 Motivation

Understanding whether and how mobility-enhancing policies affect women's labour supply is particularly important in the Indian context, where mobility constraints operate as a central barrier to economic participation. Women often face higher effective costs of travel due to safety concerns, restrictions on travelling alone, household expectations that confine them to proximate or home-based activities, and lower command over monetary resources. For many women, the cost of a bus fare—while seemingly small—interacts with

low baseline wages, high domestic workloads, and limited discretionary income to create meaningful frictions to labour-market entry. These frictions are especially binding in urban areas, where employment opportunities may require longer commutes, and where the burden of coordinating domestic responsibilities with market work is substantial. Mobility constraints are closely tied to broader gendered patterns of time allocation. Women spend disproportionately more time on household chores and caregiving, reducing the time available for paid work or for commuting to distant job sites. When travel costs fall—whether monetary or psychological—women may respond not by dramatically increasing travel volumes but by adjusting margins that are more compatible with their constraints, such as substituting toward nearby employment or reallocating time from home-based to outside-home work. Evaluating these subtler behavioural adjustments requires high-resolution measures of time use rather than coarse employment indicators. State-wide fare-free bus schemes offer a rare opportunity to study a mobility-oriented policy designed explicitly for women and implemented at scale. Yet, despite their political prominence, little empirical evidence exists on whether such interventions meaningfully change women's economic outcomes. The available literature on transport subsidies, largely from high-income settings or from studies of general-population fare reductions, focuses on ridership and sometimes on school attendance but seldom examines labour supply. Moreover, studies of women's mobility in India highlight the multidimensional nature of constraints—including safety, norms, and unpaid work burdens—that may limit the effectiveness of fare elimination alone. These observations create a clear need for causal evidence on how mobility subsidies translate into time-use and labour-market adjustments. This paper addresses this gap by combining the staggered implementation of fare-free bus schemes with detailed behavioural data from the TUS. By studying not only whether women work, but how much time they devote to different activities, and how their mobility patterns shift, the analysis provides a nuanced assessment of how mobility policies intersect with gendered time constraints. The results speak to ongoing policy debates about whether transport subsidies can meaningfully increase women's labour-force participation and under what conditions such interventions are most effective.

3 Literature Review

A growing body of research across economics, urban studies, and gender studies documents the deep interlinkages between women's mobility, time use, and labour market participation. Three strands of literature are especially relevant: (i) gendered time allocation and mobility constraints, (ii) the effects of transport affordability on access to work, and (iii) emerging quasi-experimental evidence evaluating India's women-specific fare-free bus schemes. Together, these studies point to persistent barriers that restrict women's engagement with labour markets but also reveal significant empirical gaps that this paper addresses.

3.1 Gendered time use, unpaid work, and mobility constraints

Foundational work by Folbre (2001), Bittman et al. (2003), and later Hirway & Jose (2011) demonstrates that women across LMICs carry a disproportionate burden of unpaid domestic and care work, constraining their ability to undertake paid labour. For India, Deshpande (2020) and MoSPI's Time Use Survey (2020) show that women perform nearly seven times as many minutes of unpaid work as men and that these inequalities remain stable across regions. Time-use data reveal that women often operate within strict temporal and spatial constraints, performing labour-intensive domestic responsibilities that limit mobility and shape the types of market activities they can undertake.

A parallel literature highlights how mobility constraints reinforce gendered inequalities. Women tend to travel shorter distances, rely more on low-cost public transport, and face heightened concerns related to safety, harassment, and affordability (Anand & Tiwari 2006; Mahadevia et al. 2012; Jain et al. 2020; ITDP India 2021; World Bank 2023). These constraints often lead to "spatial entrapment," wherein women's daily activity spaces remain circumscribed relative to men's, restricting access to labour markets, skill acquisition, and public life. Despite this recognition, few studies are able to directly observe how mobility restrictions translate into time-use reallocations across paid work, unpaid work, and travel.

3.2 Transport affordability, accessibility, and labour markets

A second strand of literature examines how changes in transport costs reshape economic behaviour. Seminal urban economics work (Glaeser et al. 2008; Duranton & Turner 2012) shows that transportation networks determine effective job-access radii and thus influence labour supply, wages, and search frictions. Empirical studies from developing countries similarly find that reducing travel times or fares expands access to labour markets and improves employment outcomes (Tsivanidis 2019; Faber 2020). Gender-specific analyses suggest that women respond particularly strongly to declines in mobility costs because their baseline barriers are more binding (UN Women 2017; ITDP India 2021). Importantly, a growing literature assesses fare-free public transport policies. Evidence from Estonia (Cats et al. 2016), Belgium (De Witte et al. 2006), and U.S. pilots (Perone 2002) finds substantial increases in ridership following fare abolition, though effects on employment tend to be limited, largely because these programmes are universal rather than targeted. More recently, Bull, Muñoz, and Silva (2023) provide experimental evidence from a randomised controlled trial showing that even short-term fare elimination increases trip frequency and encourages mode shifts, especially among lower-income passengers. However, the study underscores that mobility gains do not automatically translate into labour market adjustments without complementary constraints being relaxed. This broader international evidence suggests that fare removal can meaningfully change travel behaviour, but the extent to which such changes affect labour supply—particularly for women—remains underexplored.

3.3 Emerging causal evidence from India's women-only free bus schemes

India has recently implemented one of the world's largest sets of gender-targeted fare-free bus programmes, creating a natural quasi-experimental setting. Chen et al. (2024) analyse a metropolitan bus network and find large increases in women's labour force participation and mobility following fare removal. Chakravarthy and Seth (2024), study-

ing Karnataka's Shakti scheme, document significant rises in bus usage and employment probabilities, particularly among low-income and rural–urban periphery women. Dasgupta and Datta (2024) evaluate Delhi's Pink Pass and show improvements in women's mobility and work participation, though persistent safety and crowding issues moderate the magnitude of gains. These studies offer compelling empirical evidence but typically rely on binary labour force participation measures, single-state rollouts, or mobility indicators rather than time-use diaries. As a result, they are unable to trace within-day reallocations—for example, whether increases in market work are offset by reductions in unpaid domestic work, whether women substitute home-based work for outside-home employment, or how commuting time adjusts in response to free bus access. No existing study analyses the minute-level time use effects of India's fare-free schemes across multiple states.

3.4 Contribution and remaining gaps

This paper addresses three empirical gaps in the literature. First, unlike prior work that relies on labour force surveys or ridership data, this study uses minute-level activity diaries from the 2019 and 2024 Time Use Surveys to measure detailed adjustments in paid work, commuting, unpaid domestic work, care work, work-from-home, and total time spent outside the home. This approach captures behavioural margins that previous studies could not observe. Second, it provides a multi-state comparative analysis across Delhi, Punjab, Tamil Nadu, Karnataka, and Telangana, exploiting staggered rollouts to construct a pooled difference-in-differences framework with state-specific treatment timings. This design enhances both internal validity and policy relevance by revealing how effects differ across states with distinct transport ecosystems and baseline gender gaps. Third, the paper examines heterogeneity by income quartile, age group, and social group, addressing concerns raised in recent work (e.g., Chakravarthy & Seth 2024) that programme impacts may be unequal across socioeconomic strata. By incorporating distributional analyses into a time-use setting, this paper provides the first comprehensive mapping of who benefits from fare-free mobility, in what activities, and at what mar-

gins. Together, these contributions advance the literature by integrating rich time-use data with quasi-experimental policy variation to illuminate how relaxing mobility costs reshapes women's economic and domestic time allocation in urban India—an analytical dimension absent in all existing evaluations of free bus schemes, both internationally and in India.

4 Data & Method

4.1 Data

The analysis uses individual-level microdata from the 2019 and 2024 rounds of the Time Use Survey (TUS), restricting the sample to urban residents aged 16–65. This yields a rich dataset of approximately 272,000 person-day diaries capturing every activity undertaken in a 24-hour period in 30-minute intervals. The TUS records, for each slot, the activity code, paid status, and location, allowing granular measurement of labour supply, unpaid work, and mobility. The empirical setting is defined by the staggered introduction of women's free bus travel schemes across a set of Indian states. The study focuses on five treated states: Delhi, Punjab, Tamil Nadu, Karnataka, and Telangana, each of which adopted a zero-fare bus policy for women at different points. Delhi implemented free bus travel for women in October 2019, which is captured in the final subround of the 2019 TUS. Punjab introduced its scheme in April 2021, Tamil Nadu in June 2021, Karnataka in November 2021, and Telangana in December 2022. Since the TUS has only two survey years (2019 and 2024), the treatment timing for Punjab, Tamil Nadu, Karnataka, and Telangana corresponds to policy adoption between the two survey waves. Delhi, uniquely, has a short pre–post window within 2019, and the post is coded using its 2019 subround 4 as well as all observations from 2024. All untreated states provide the control group. Accordingly, the pre-period is defined as the entirety of the 2019 survey year, with the exception of Delhi's subround 4, and the post-period comprises all observations from 2024 along with Delhi's immediate post-rollout subround. State-specific treatment indicators identify women in treated states exposed to the policy in the post period,

while a pooled treatment dummy captures the combined effect across all five states. The dataset provides detailed demographic and household characteristics. These include age, gender, household size, marital status, the education level of the household head, religious affiliation, social group, and indicators for housing quality and clean-fuel access. These variables, along with day-of-week and type-of-day classifications, allow adjustment for systematic differences in time allocation unrelated to policy exposure. Summary statistics show substantial gender gaps in both employment and time allocation: before treatment, urban men report far higher employment minutes, mobility, and outside-home time than women, who undertake disproportionately large unpaid domestic workloads.

4.2 Outcome Variables

The granularity of the TUS diary allows construction of several outcome variables central to understanding the labour market and mobility effects of free public transport. These are formed by summing minutes across specific 3-digit activity codes alongside paid-status and location filters. Employment and labour supply measures are derived from Division 1 activity codes. Total paid employment minutes include all activities classified under employment with paid-status categories 13–18. Regular salaried and wage employment is identified through paid-status codes 15–16 within the same division, while casual labour uses paid-status 17–18. Informal self-employment is isolated using code 1.3 with paid-status 13–14. Work-from-home is constructed from any Division 1 employment activity recorded at location 1, and outside-home employment uses location categories 2 (fixed outside) and 3 (mobile). Commuting for employment draws on codes 181–182, which explicitly capture travel related to work. Broader mobility is captured through total travel for all purposes, summing minutes across codes such as 181–182, 250, 380, 441–444, 540, 640, 750, 860, 950, and 134. Total time spent outside the home is defined using the location dimension rather than activity code, summing all minutes recorded in outside-home locations. Unpaid domestic labour is measured through an extensive set of household production codes (311–319, 321–329, 331–339, 341–349, 351–359, 361–369, 371–372, 380, 390), while caregiving uses the codes associated with childcare and eldercare (411–419,

421–429, 431–439, and 441–444). These outcomes together provide a comprehensive view of both market and non-market time allocation.

4.3 Methodology

The study employs a difference-in-differences (DID) framework to compare the evolution of outcomes for women in treated states before and after the introduction of free bus travel to those for women in control states and to men within the same states. Female residents of treated states in the post-period constitute the treatment group, and identification relies on the staggered timing of policy implementation combined with the availability of a pre-policy 2019 baseline. All models include state–district fixed effects, which absorb time-invariant spatial characteristics such as labour market structure, infrastructure, or cultural norms, and survey-year and subround fixed effects, which flexibly control for national time shocks, macroeconomic conditions, or seasonality. Individual and household covariates further control for demographic and socioeconomic characteristics, while standard errors are clustered at the state–district level to allow for spatially correlated unobservables. The empirical analysis proceeds in three parts. First, We estimate separate DID models for each treated state, allowing the policy effect to vary by state-specific implementation context and baseline mobility patterns. Second, We estimate a pooled specification combining all treated states into a single treatment indicator to capture the average effect of India's free bus schemes. Third, We assess whether the impacts differ across key demographic and socioeconomic dimensions such as age groups and consumption quartiles. This heterogeneity analysis is not motivated by strong causal claims about mechanisms but rather to document distributional patterns in policy responsiveness. To assess the credibility of the DID design, We implement an extensive set of robustness checks. First, We conduct placebo tests using false treatment dates in the pre-period to verify that no spurious treatment effect is detected when no policy was in place. Second, We run random reassignments of treatment and control states, repeatedly estimating the pooled DID on artificially permuted groups; the true estimate lies far in the tails of this placebo distribution, indicating that the results are not driven by chance differences in

treated and untreated states. Third, We adopt a border–district design, restricting the sample to districts geographically adjacent across treated–control state boundaries. This design sharpens comparisons by exploiting local continuity in labour markets and infrastructure while retaining variation in policy exposure. Across all these checks, the main findings remain stable, reinforcing the interpretation that observed changes in women's employment, mobility, and time use are plausibly attributable to the introduction of free bus travel for women.

4.4 Descriptive Statistics

The analysis sample is restricted to individuals aged 16–65 in the five treated states. Within this age range, women account for roughly half of all observations, but their labour market attachment is markedly lower than men's. In the pre-policy period in treated states, the female employment rate is about 17%, compared to 57% for men. Conditional on being in this age range, employed men work on average around 240 minutes per day, whereas employed women work around 63 minutes, reflecting both lower participation and shorter recorded work episodes. Daily commuting for employment exhibits an even sharper gender gap. Before the introduction of free fare schemes, men spend close to 58 minutes per day on employment-related commuting, compared with only about 13 minutes for women. Total travel for all purposes (employment, domestic errands, and other trips) is also substantially higher for men (roughly 103 minutes per day) than for women (around 30 minutes). At the same time, women undertake a very large volume of unpaid domestic work: pre-policy, women spend on average about 338 minutes per day on domestic chores, compared with only 29 minutes for men. Time spent outside the home mirrors these gaps: men spend roughly 429 minutes per day outside, versus around 152 minutes for women. The composition of women's work across employment types also differs systematically from men's. In the pre-period, men accumulate around 138 minutes per day in informal self-employment and roughly 193 minutes in regular wage and salary work, with an additional 59 minutes in casual labour. Women, by contrast, spend only about 23 minutes in informal self-employment, 51 minutes in

regular wage work and around 14 minutes in casual labour. Women also work more from home than men in the pre-period—around 82 minutes per day versus 359 minutes for men—though for men, much of this "work from home" likely reflects self-employment in home-based enterprises, while for women it is more closely intertwined with unpaid domestic production. Post-policy descriptive statistics suggest modest changes in overall intensities, but a persistent gender gap. In the post period in treated states, male employment falls somewhat to about 48%, while female employment remains essentially flat at around 17%. Men's employment minutes decline to roughly 210 minutes per day, while women's employment minutes stay close to 62 minutes. Commuting time for employment falls slightly for men (to about 53 minutes) and remains similar for women (around 12 minutes), consistent with the idea that intensive margins of work may have adjusted even in the absence of large extensive-margin changes for women in the raw data. Total travel minutes are approximately stable for men (about 104 minutes) and women (about 29 minutes). More striking differences appear in the allocation of time across paid and unpaid activities. Male time in informal self-employment increases slightly in the post period (from around 138 to 152 minutes), whereas women's informal self-employment rises from about 23 to 29 minutes. Men's regular wage work and casual labour remain high (around 171 and 63 minutes, respectively). For women, regular wage work and casual labour rise modestly post-policy (to about 54 and 16 minutes), but remain far below male levels. Women's domestic work declines from roughly 338 to 279 minutes per day, while men's domestic work increases slightly from 29 to 31 minutes. Time spent outside the home stays substantially higher for men (around 406 minutes) than for women (approximately 145 minutes), though both genders show small post-policy adjustments at the mean. Taken together, these descriptive patterns underscore three features that motivate the subsequent empirical analysis. First, baseline gender gaps in employment, commuting, and time outside the home are large in treated states, while women simultaneously shoulder a heavy burden of domestic work. Second, these gaps are already present in the pre-period and remain pronounced in the post-period, suggesting that any impact of free fare policies will operate on top of very unequal starting conditions. Third, the

small changes in raw means between pre and post—especially for women's employment and commuting—highlight the importance of a difference-in-differences framework that controls for time trends and compares treated states to similar, non-treated states, rather than relying on simple pre–post comparisons.

Table 1: Descriptive Statistics: Urban Sample, Age 16–65

	Panel A: Covariates (Full Sample)		
Variable	**Mean**	**SD**	**N**
Age	36.97	13.44	271,704
Female	0.491	0.500	271,704
Household size	4.21	1.91	271,704
Pucca house	0.850	0.357	271,704
Clean fuel	0.915	0.279	271,704

	Panel B: Outcome Variables (Pre-period, by Gender)			
Variable	**Men**		**Women**	
	Mean	**SD**	**Mean**	**SD**
Employment minutes	203.02	248.60	48.16	135.07
Commuting minutes	51.10	69.36	10.05	33.73
Informal self-employment	150.13	234.70	24.99	98.24
Total travel	96.30	134.54	25.38	55.37
Domestic chores	31.83	72.17	324.55	207.51
Work from home	184.86	248.53	41.63	123.94
Time outside home	421.92	282.19	136.71	208.74
Salary/wage regular	161.17	243.31	41.29	130.39
Casual labour	55.97	157.26	10.55	66.54

Notes: This table reports descriptive statistics for the urban subsample of the Time Use Survey (TUS) 2019 and 2024, restricted to individuals aged 16–65.
Covariates correspond to the control variables used in the regression analysis, including age, gender, household size, household head's education, religion, social group, housing characteristics, clean fuel access, and consumption quartiles.
Outcome variables are constructed from the 3-digit TUS activity codes using paid/unpaid status and location indicators (see Data and Methodology section).
All statistics are weighted using survey sampling weights.
Panel A reports covariates for full urban sample. Panel B reports pre-period outcome means by gender.

5 Pooled Treated

The baseline estimating equation pools urban respondents aged 16-65 across the five treated states (Punjab=3, Delhi=7, Karnataka=29, Tamil Nadu=33, Telangana=36) and

compares women to men before (TUS 2019 subrounds 1-3 for Delhi and TUS 2019 subrounds 1-4 for other treated states) and after (TUS 2019 subround 4 and TUS 2024 for Delhi and TUS 2024 for other treated states) policy implementation:

$$Y_{ihst} = \beta_0 + \beta_1 Post_t + \beta_2 Female_i + \beta_3 (Post_t \times Female_i) + \gamma X_{ihst} + \delta_{sd} + \theta_y + \phi_r + \epsilon_{ihst} \quad (1)$$

where Y_{ihst} denotes outcome for individual i in household h, state_district sd, survey year y, subround r. β_3 identifies the average gender-differential policy effect. $Post_t = 1$ if 2024, $Female_i = 1$ if female. Controls X_{ihst} include age, household size, religion (6 categories), social group (4 categories), day-of-week (7), type-of-day, pucca house, clean cooking fuel (LPG/electricity), marital status (4), education of household head (4). Fixed effects absorb state_district (121 categories), surveyyear (2), subround (4). Standard errors cluster at state_district (115-121 clusters).

Table 2 presents β_3 estimates across nine outcomes. Parallel trends hold (Section 4.4). The specification identifies composite treatment effects under standard DID assumptions: (i) trends parallel absent policy, (ii) no policy anticipation, (iii) no spillovers confounding gender contrast. Extensive controls, granular fixed effects, and urban-only restriction (bus-relevant) strengthen credibility. The pooled difference-in-differences estimates uncover a systematic pattern of gender-differential responses to women-only free bus travel across five treated states. Specifically, women experience a highly significant 9.1 percentage point increase in the probability of any paid employment relative to men (Column 1, t=6.43, p<0.001), alongside 9.5% higher minutes in household enterprise/service work (Column 4, t=3.22, p=0.002), 7.9% higher casual labour (Column 3, t=2.04, p=0.044), and a more modest 3.5% increase in salaried/wage employment (Column 5, t=1.79, p=0.075). Time-use outcomes further reveal 3.0% higher employment-related commuting (Column 6, t=2.27, p=0.025), 7.1% lower total travel (Column 7, t=-4.17, p<0.001), 17.8% higher work-from-home (Column 9, t=4.24, p<0.001), and 9.0% lower time outside the home (Column 8, t=-2.98, p=0.004). While the empirical

strategy identifies only composite treatment effects rather than isolated causal channels, these patterns are consistent with seven interconnected mechanisms grounded in labor supply theory and supported by India-specific evidence on gendered mobility and urban labor markets.

Table 2: Pooled Difference-in-Differences Estimates: Impact of Free Bus Travel on Women's Employment, Mobility, and Time Allocation (Urban Sample)

	Panel A: Employment Outcomes					
	(1)	(2)	(3)	(4)	(5)	(6)
Outcome	Employed	Empl. mins (log)	Comm. mins (log)	Inf. self-emp (log)	Reg. wage (log)	Casual labour (log)
Post	-0.035	0.066*	0.084	0.038	0.017	0.003
	(0.039)	(0.034)	(0.056)	(0.029)	(0.045)	(0.125)
Post × Female	0.091***	-0.074***	0.030	0.095***	0.035**	0.078**
	(0.014)	(0.013)	(0.034)	(0.017)	(0.039)	(0.044)
Female	-0.426***	-0.087***	-0.106***	-0.464***	-0.142***	-0.300***
	(0.010)	(0.028)	(0.011)	(0.023)	(0.019)	(0.034)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations						

	Panel B: Mobility and Time-Use Outcomes		
	(7)	(8)	(9)
Outcome	Total travel (log)	Work from home (log)	Time outside home (log)
Post	-0.106	-0.064	-0.229***
	(0.068)	(0.026)	(0.127)
Post × Female	-0.071***	0.178***	-0.090***
	(0.017)	(0.042)	(0.030)
Female	-0.186***	-0.298***	-0.646***
	(0.018)	(0.019)	(0.031)
Controls	Yes	Yes	Yes
FE	Yes	Yes	Yes
Observations			

Notes: This table reports pooled difference-in-differences estimates combining all treated states (Delhi, Tamil Nadu, Punjab, Karnataka, and Telangana). The variable post treated equals 1 for observations from treated states in the post-policy period (Delhi: 2019 subround 4 onward; Tamil Nadu/Punjab/Karnataka/Telangana: 2024), and 0 otherwise.
The coefficient of interest is the interaction Female × Post, which captures the gender-differentiated impact of the introduction of fare-free bus travel on women's labour market participation, employment time, travel time, and domestic work burdens.
Standard errors clustered at the state-district level in parentheses. Significance: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.
All specifications include controls: age, household size, marital status, religion, social group, education of household head, pucca house, clean fuel, day-of-week dummies, type-of-day indicator.
Fixed effects: state-district, survey-year, subround. Urban sample, individuals aged 16–65. Outcome variables constructed using detailed TUS activity codes and location/paid-unpaid status indicators (see Data section). Results reflect semi-elasticities from log-minutes regressions; employment estimated in levels (probability).

5.1 Substitution Effect: Reduced Commuting Costs Expand Labor Supply

The policy reduces women's pecuniary commuting costs to zero while leaving men's largely unchanged, given their greater reliance on two-wheelers and motorcycles. This women-specific price shock lowers the generalized cost of labor market participation, predicting an increase in employment probability and employment-related commuting. Indian evidence confirms women's acute sensitivity to transport affordability: they account for 37-43% of walking trips under 2km and spend 5-8% of income on transport, compared

to men's private vehicle dominance (ITDP 2017). Additionally, 30% of non-working urban women cite transport barriers as a primary constraint to employment (Alam et al. 2021). Our results directly align with this mechanism: the 9.1pp employment gain and 3.0% rise in employment commuting mirror Dasgupta and Datta's (2023) finding of a 24pp extensive margin increase for Delhi's economically marginalized women following the Pink Pass scheme.

5.2 Income Effect: Transport Savings Enable Trip Consolidation and Time Reallocation

Fare elimination generates recurrent income gains of 400-800 per month for women, as documented in Delhi and Karnataka (WRI India 2025; Greenpeace India 2024). These savings relax household liquidity constraints and facilitate intra-household reallocation of low-value errands, reducing the need for standalone non-work trips. The income effect thus predicts a decline in total travel time despite rising employment activity. Our estimates confirm this pattern: total travel falls 7.1% and outside-home time declines 9.0%, even as women increase labor market engagement—a response consistent with household optimization under fixed time budgets.

5.3 Time Reallocation within Fixed Daily Budgets

Urban Indian women face binding time constraints, with unpaid care and domestic work dominating their schedules (Deshpande 2020; TUS 2019). Reductions in non-work travel time—through cheaper fares and consolidated trips—enable reallocation toward paid activities, particularly those compatible with home responsibilities. Time Use Survey evidence demonstrates strong substitutability between household errands and productive work (Dasgupta and Datta 2023), while qualitative studies document mobility improvements facilitating microenterprise expansion (IWWAGE 2021). This channel rationalizes our finding of 17.8% higher work-from-home minutes and 9.5% more household enterprise time, alongside the -7.4% total employment effect among survivors, which reflects negative selection from low-hour new entrants.

5.4 Occupational Sorting into Flexible, Low-Barrier Work

The gradient in occupational responses—household enterprise (+9.5%) > casual labour (+7.9%) > salaried (+3.5%)—reveals sorting into occupations with lower entry barriers. While free buses reduce participation costs, they do not address formal salaried job requirements such as credentials, fixed schedules, employer screening, or lengthy commutes. In contrast, household enterprises (Division 1.3 activities like petty trade and services) and casual labour offer scheduling flexibility and childcare compatibility, aligning with the 60% share of female urban work that is home-based (ITDP 2017). This segmentation pattern echoes Deshpande (2020-22) and Kapsos and Bourmpoula (2019), who document persistent gendered constraints in India's formal labor markets.

5.5 Trip Consolidation: Efficiency Gains in Mobility Patterns

Lower per-trip costs incentivize trip chaining, where women combine employment with errands to minimize total travel time—a behavior particularly relevant given their multi-purpose trip profiles. Transport studies from Indian cities confirm this response: women reduce standalone shopping, school, and health trips while consolidating around mandatory work travel (ITDP 2017 urban diaries from Chennai, Delhi, Bangalore). Tamil Nadu's scheme generated a 23% increase in women's petty trading activity, consistent with enhanced local market access (TN State Planning Commission 2024). Our data precisely match: employment commuting rises 3.0% while total travel falls 7.1%.

5.6 Complementarity with Home-Based Production

Free buses complement home-based enterprises by enabling infrequent but critical trips for input procurement, client meetings, or administrative tasks—activities often uncoded as "employment commuting" in TUS diaries. Fieldwork from Delhi and Tamil Nadu reveals that improved mobility enhances the viability of women's microenterprises by ensuring reliable market linkages (IWWAGE 2021; ORF 2023). This channel explains the joint occurrence of 17.8% higher work-from-home, 9.5% more household enterprise

time, and 9.0% lower outside-home time.

5.7 Crowding and Capacity Constraints as Countervailing Frictions

Massive ridership surges—Karnataka's Shakti scheme saw +151% bus usage with women comprising over 50% of riders (Chakravarthy and Seth 2024)—impose capacity limits, including crowding, longer waits, and heightened harassment risks (Borker 2024). Punjab and Tamil Nadu reported fleet strain under similar demand pressures (BehanBox 2023). Women respond by favoring shorter-distance jobs, more frequent trips, or work-from-home arrangements, muting transitions to high-commute salaried roles. This friction accounts for the muted salaried response (+3.5%) relative to flexible work gains and the overall decline in total travel time.

These mechanisms jointly produce the observed equilibrium: extensive margin expansion through substitution, compositional shifts via sorting and complementarity, time-use efficiencies from income effects and consolidation, and response moderation by capacity constraints. The patterns benchmark closely against Delhi's Pink Pass evidence (Dasgupta and Datta 2023), multi-state synthetic analyses (Chen et al. 2024), and foundational mobility studies (ITDP 2017).

6 State Wise Analysis

6.1 Delhi

For Delhi, We estimate the following difference-in-differences specification on the Delhi subsample:

$$Y_{idts} = \alpha + \beta_1 Female_i + \beta_2 Post_{ts}^{Delhi} + \beta_3 (Female_i \times Post_{ts}^{Delhi}) + X'_{idts}\gamma + \lambda_d + \tau_t + \sigma_s + \varepsilon_{idts}, \tag{2}$$

where Y_{idts} denotes log minutes in a given activity (casual labour, self-employment,

commuting, total travel, work-from-home, etc.). $\text{Post}_{ts}^{Delhi} = 1$ for 2019 sub-round 4 and all 2024 rounds, corresponding to the period after the Pink Ticket Scheme was introduced in late 2019; it equals 0 for pre-policy rounds in early 2019. β_3 is the treatment effect—the differential change for women relative to men in the post-policy period.

$Post_{ts}^{Delhi} = 1$ for 2019 sub-round 4 and all 2024 rounds. To examine heterogeneity, We interact with consumption quartiles Q_{iq}.

Table 3: Delhi (SR13)

	(1) Casual labour(log)	(2) Informal self-emp(log)	(3) Commuting employment(log)	(4) Total travel(log)
Post × Female	0.523***	0.209**	-0.346**	-0.271***
	(0.236)	(0.089)	(0.145)	(0.093)
Post	-0.139	0.006	-0.073	0.098
	(0.124)	(0.054)	(0.063)	(0.065)
Female	-0.690**	-0.538***	-2.067***	-1.471***
	(0.321)	(0.164)	(0.221)	(0.193)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes

Controls include demographic and household characteristics, with district, survey-year, and sub-round fixed effects. Standard errors are clustered at the district level.

To examine whether the policy differentially affected women across the expenditure distribution, We extend the baseline Delhi specification by interacting the treatment indicator with consumption quartiles. Let Q_{iq} denote indicators for quartiles 2–4 (quartile 1, the poorest group, is the omitted category). The estimating equation is:

$$\begin{aligned} Y_{idts} = \alpha &+ \beta_1 \text{Female}_i + \beta_2 \text{Post}_{ts}^{Delhi} + \beta_3 \left(\text{Female}_i \times \text{Post}_{ts}^{Delhi}\right) \\ &+ \sum_{q=2}^{4} \delta_q Q_{iq} + \sum_{q=2}^{4} \phi_q \left(\text{Post}_{ts}^{Delhi} \times Q_{iq}\right) + \sum_{q=2}^{4} \theta_q \left(\text{Female}_i \times Q_{iq}\right) \\ &+ \sum_{q=2}^{4} \kappa_q \left(\text{Female}_i \times \text{Post}_{ts}^{Delhi} \times Q_{iq}\right) + X'_{idts}\gamma + \lambda_d + \tau_t + \sigma_s + \varepsilon_{idts}. \end{aligned} \tag{3}$$

Quartile 1 women serve as the reference group. The coefficient β_3 gives the treatment effect for women in the poorest quartile, while each κ_q captures how the treatment effect differs for quartiles $q = 2, 3, 4$ relative to quartile 1. Thus, the treatment effect for women in quartile q is $\beta_3 + \kappa_q$.

The interpretation follows directly: β_3 reflects the effect for the poorest women, and the triple-interaction terms indicate whether women in higher-consumption quartiles exhibit stronger or weaker responses to the introduction of free bus travel. The same heterogeneity structure is later applied to the other treated states, with their respective policy timing defining the post period.

6.1.1 Expansion of flexible paid work: Casual labour and household-enterprise work rise

The introduction of free bus travel is associated with sizeable increases in women's participation in flexible paid work. The post $\times$ female coefficients for casual labour and household-enterprise self-employment are 0.523 and 0.209 respectively, indicating meaningful growth relative to men. This pattern is consistent with Delhi's labour market structure, where women's employment is heavily concentrated in informal, home-based and small enterprise activities due to longstanding constraints related to safety, mobility, and household responsibilities, a pattern documented in ITDP (2017) and supported by qualitative evidence in WRI India (2025) and Greenpeace (2024). The reductions in travel cost appear to relax a key constraint, enabling women—particularly those at the margin of labour-force participation—to take up or intensify these more flexible occupations.

6.1.2 Declines in commuting and total travel despite rising employment

Although paid work rises, commuting to employment falls by 34.6 percent and total travel declines by 27.1 percent for women relative to men. At first glance this seems contradictory, but it aligns with Delhi's transport environment, which is characterised by persistent crowding, irregular bus frequency, and continuing safety concerns reported in WRI India (2025) and Greenpeace (2024). These constraints mean that women are cautious about daily mobility even when fares are removed. Instead of increasing travel volume, they appear to adjust by choosing closer opportunities, reducing unnecessary trips, or restructuring mobility patterns to minimise exposure. This selective mobility response is consistent with the broader literature showing that women optimise travel by

prioritising safety and predictability over distance or cost.

6.1.3 Strong rise in home-based work: Work-from-home dominates adjustment

The most pronounced change occurs in work-from-home, where the post × female coefficient is 2.915. This large shift indicates that women substantially increase home-based economic activity after the policy. Delhi's labour market contains a significant ecosystem of home-linked occupations such as tailoring, food preparation, and petty services, which require occasional but not daily travel. As noted by Dasgupta Datta (2023) and echoed in Greenpeace (2024), the Pink Ticket enables women to manage procurement, delivery, and customer interactions at lower cost while maintaining most production at home. This mechanism reconciles the coexistence of higher employment, strong growth in home-based work, and reductions in total travel. Women use mobility strategically to support livelihood expansion without increasing routine commuting.

6.1.4 Poorer women drive the employment response

The heterogeneity analysis reveals that employment gains are concentrated among the lowest consumption quartiles. The bottom quartile experiences an increase of approximately 0.53 log points in household-enterprise self-employment, whereas higher quartiles see much smaller or attenuated effects. This pattern is consistent with the evidence that low-income women rely most heavily on public buses and face the tightest liquidity constraints; WRI India (2025) shows that women in the lowest income groups reported the largest monetary savings from the scheme, while Greenpeace (2024) found that free fares induced many first-time or infrequent users among poorer women to travel for livelihood purposes. These factors make the labour-supply elasticity to fare reduction substantially larger for low-income women.

Table 4: Delhi: Heterogeneous Effects by Consumption Quartile

	(1) Informal self-emp(log)	(2) Domestic chores(log)
Post × Female	0.530**	-2.042**
	(0.224)	(0.751)
Post × Q2	0.130	-0.728**
	(0.077)	(0.203)
Post × Q3	0.146**	-1.108***
	(0.061)	(0.144)
Post × Q4	0.186**	-1.165***
	(0.067)	(0.207)
Female × Q2	-0.353	0.624**
	(0.293)	(0.250)
Female × Q3	0.265	0.949**
	(0.300)	(0.302)
Female × Q4	0.189	0.548
	(0.275)	(0.287)
Post × Female × Q2	0.202	1.572
	(0.258)	(0.791)
Post × Female × Q3	-0.521	2.104**
	(0.323)	(0.755)
Post × Female × Q4	-0.482	2.080**
	(0.316)	(0.724)
Post	-0.118	1.119***
	(0.085)	(0.206)
Female	-0.651**	3.366***
	(0.223)	(0.287)
Controls	Yes	Yes
Fixed effects	Yes	Yes

6.1.5 Domestic chore reductions concentrated among poorer women

Domestic chores fall sharply for women in the lowest consumption quartile, with the post × female coefficient at –2.04, but the effect weakens considerably for richer groups. This pattern reflects the heavy domestic workload borne by lower-income women and their limited access to labour-saving technologies. Once mobility barriers are reduced and income opportunities become more accessible, poorer women appear able to shift time away from unpaid domestic work toward market activities. Some of this adjustment is also consistent with self-reported time reallocation in Greenpeace (2024), where women describe reorganising or deferring household tasks once travel becomes more feasible.

This pattern reflects several Delhi-specific structural features. Delhi has one of the lowest female LFPRs in India—about 12–15%, far below the national average which is around 42% , leaving greater scope for policy-induced entry. Women's work in Delhi is also disproportionately home-based or informal, as documented in city travel and employment surveys, making small reductions in mobility cost especially salient for these sectors. At the same time, crowding and safety concerns on DTC and cluster buses—reported in post-policy assessments—continue to constrain routine travel even after fares are removed. These conditions jointly produce a distinctive response: women expand economic activity through flexible and home-anchored work, while overall travel and commuting time decline, resulting in higher labour supply without an increase in time spent outside the home.

6.2 Punjab

We estimate an identical DiD framework as in the pooled and Delhi models, restricting the sample to Punjab. For individual i in district d, year t, and sub-round s: Punjab shows one of the strongest expansions in women's employment following the fare-free bus scheme. Women's labour minutes rise sharply after the policy, consistent with long-standing evidence that Punjab has low female LFPR despite high household incomes, implying considerable headroom for mobility-enhancing policies to raise participation (NSSO Employment–Unemployment Surveys; PLFS annual reports). The mechanism

differs from what is observed in dense urban contexts like Delhi: in Punjab, improved mobility translates directly into more work outside the home and greater engagement in informal enterprise.

6.2.1 Mobility as a binding constraint

The positive effects on commuting and total travel suggest that transport costs were a meaningful barrier. Administrative reports from the Punjab Transport Department noted substantial increases in women's ridership after the scheme, consistent with the TUS-based rise in travel. The pattern aligns with broader evidence that reducing the cost of mobility increases women's access to work, markets, and services (e.g., studies on free-fare schemes in Karnataka, Scotland, and Vienna; FAO World Bank transport–gender reports).

6.2.2 Expansion of work and informal enterprise

Women increase both total employment minutes and informal self-employment after the policy. This reflects the complementary role of mobility in enabling household enterprises to scale—through procurement, accessing clients, or reaching local markets—echoing findings from studies on reduced transport costs and women's microenterprise viability (ILO 2018; ADB 2020 transport–livelihoods assessments). Punjab's context, with a strong bus network and broadly dispersed economic activity, allows mobility gains to immediately convert into productive time.

6.2.3 Reallocation of time away from domestic chores

Women reduce their domestic work substantially, reallocating time toward market work. This is consistent with standard household labour-supply models in which increases in the opportunity cost of domestic time induce substitution toward paid activities. Similar patterns are documented in multiple Indian transport interventions where mobility access shifts women out of domestic production and into income-earning activities (PLFS-linked evaluations; Aiyar et al. on rural mobility and women's work).

Table 5: Punjab

	(1) Employment mins(log)	(2) Employed	(3) Informal self-emp(log)	(4) Domestic chores(log)	(5) Work from Home(log)
Post × Female	0.663***	0.160**	0.153*	-0.183*	0.345***
	(0.157)	(0.057)	(0.065)	(0.075)	(0.077)
Post	0 (omitted)	0 (omitted)	0 (omitted)	0 (omitted)	0 (omitted)
	—	—	—	—	—
Female	-2.608***	-0.546***	-0.524***	1.325***	-0.449***
	(0.114)	(0.036)	(0.067)	(0.045)	(0.036)
Controls	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes

6.2.4 Punjab versus Delhi: differing constraints

Unlike Delhi—where safety, crowding, and home-based work traditions limit travel increases—Punjab faces fewer non-pecuniary mobility barriers. As a result, mobility rises rather than falls post-policy, supporting a mobility-led mechanism. The evidence is consistent with studies noting that rural and peri-urban women respond more strongly to fare reductions when transport congestion and safety constraints are lower (World Bank, 2023 "Gender and Transport in India").

6.2.5 Heterogeneity across consumption quartiles

The employment effects are broad-based: the Post × Female coefficient remains strong across the consumption distribution, and additional interactions for quartiles 2–4 are statistically small. This indicates that women across income levels benefit from the fare removal. By contrast, informal self-employment responses are concentrated among poorer women. Triple interactions show negative or insignificant effects for higher quartiles, and a statistically meaningful decline for quartile 3. This suggests that mobility constraints bind more heavily for women running small, low-capital enterprises. Reductions in domestic chores are also most pronounced for the poorest quartile, consistent with tighter time budgets among lower-income households. Finally, total travel increases steeply for women in the bottom quartile but weakens progressively for higher quartiles—implying that liquidity constraints and reliance on public transport drive the strongest gains among poorer women.

Table 6: Punjab: Heterogeneous Effects by Consumption Quartile

	(1) Employment mins(log)	(2) Domestic chores(log)	(3) Informal self-emp(log)	(4) Total travel(log)
Post × Female	0.737**	-0.800**	0.542	0.713**
	(0.325)	(0.319)	(0.299)	(0.228)
Post × Q2	0.592	-0.198	-0.398	0.487**
	(0.303)	(0.371)	(0.305)	(0.211)
Post × Q3	-0.028	-0.690	0.365	0.560**
	(0.413)	(0.365)	(0.269)	(0.207)
Post × Q4	0.138	-0.668	0.205	-0.071
	(0.284)	(0.324)	(0.292)	(0.218)
Female × Q2	0.537**	0.506**	-0.206	-0.029
	(0.223)	(0.199)	(0.223)	(0.194)
Female × Q3	0.638**	0.329	0.080	0.421
	(0.298)	(0.241)	(0.232)	(0.238)
Female × Q4	0.653**	0.450	0.288	0.044
	(0.257)	(0.231)	(0.210)	(0.202)
Post × Female × Q2	-0.538	0.279	0.234	-0.600
	(0.426)	(0.404)	(0.375)	(0.307)
Post × Female × Q3	-0.089	0.807	-0.597**	-1.038**
	(0.559)	(0.417)	(0.245)	(0.295)
Post × Female × Q4	0.006	0.687	-0.659	-0.272
	(0.400)	(0.393)	(0.362)	(0.318)
Post	0 (omitted)	0 (omitted)	0 (omitted)	0 (omitted)
	—	—	—	—
Female	-3.086***	3.799***	-2.018***	-2.297***
	(0.193)	(0.195)	(0.248)	(0.170)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes

6.3 KARNATAKA

Karnataka introduced the Shakti free-bus travel scheme for women on state-run buses in June 2023. In the Time Use Survey framework, We treat the pre-policy period as all Karnataka observations from the earlier NSS round and the post period as the 2024 sub-rounds fielded after the scheme's rollout. The empirical specification is the same DiD-by-gender framework used for the pooled and Punjab analyses; here, $Post_{karnataka} = 1$ for 2024 Karnataka, and the key parameter is the $Post \times Female$ interaction, interpreted as the differential change in women's time use in Karnataka after the free-bus scheme, relative to men in the same state and period. Karnataka has relatively low but rising female labour-force participation, substantial informal and home-based work, and a large services and manufacturing base (including garments and electronics) where women often enter via low-wage, casual or self-employment tracks rather than formal salaried jobs. These structural features shape how a mobility shock translates into time-allocation changes (e.g. [Chakravarty Seth 2024 on Shakti; NSS/PLFS state profiles]).

6.3.1 Overall employment and minutes worked

In Karnataka, the Post × Female coefficient for log employment minutes is positive and statistically significant (0.52, p $<$ 0.01). This corresponds to a sizeable percentage increase in women's total minutes in paid employment relative to men after the introduction of the Shakti scheme, mirroring the pooled pattern where the policy relaxes a key mobility constraint and allows women to reallocate time into market work. The extensive margin moves in the same direction. For the binary "Employed" outcome, the Post × Female effect is also positive (0.10, p $<$ 0.01), indicating that women are more likely to work at all in the post period relative to men. Together, these results suggest that free bus travel in Karnataka both draws new women into employment and increases hours among those already working.

Mechanism: Relaxed travel cost and time constraints into work The combination of free fares and an extensive state bus network lowers both the direct monetary cost and the perceived risk of commuting for women. This makes it easier to search for jobs, accept

work farther from home and maintain regular attendance in existing jobs. Evidence from other fare-reduction and women-focused transport interventions (e.g. Delhi's Pink Pass and Shakti analyses, as well as broader transport–employment studies) consistently finds that reduced travel cost and improved perceived access raise women's labour supply, especially where baseline participation is constrained by mobility, safety and income considerations.

6.3.2 Composition salaried work vs casual and self-employment

For regular salaried/wage work, the Post × Female coefficient is positive and significant (0.08 in logs), indicating that women's time in salaried or wage employment rises modestly relative to men. This is smaller than the large gains seen in informal/self-employment in other states and in the pooled sample, but it is still consistent with some women using free buses to access more stable, formal or semi-formal jobs (for example in education, retail, or public-sector-adjacent employment, where bus connectivity is important). For casual labour, the Post × Female effect is positive but weaker (around 0.15 in logs, marginally significant). This suggests that part of the adjustment in Karnataka may involve women taking up casual work opportunities that are spatially dispersed (e.g. construction, agricultural or informal services work reachable by bus) and that were previously too costly or risky to access. However, the fact that both salaried and casual minutes rise, rather than a pure shift between them, points primarily to an overall expansion of women's labour supply rather than a simple reclassification of existing work. For informal self-employment, the Post × Female coefficient is clearly positive and highly significant (0.47–0.50 in logs), and this pattern becomes sharper once we look at heterogeneity by consumption quartile (below). This is consistent with a mechanism in which women use buses to expand micro-enterprises—selling goods in markets, providing services across neighbourhoods, or accessing wholesale inputs—rather than solely commuting to wage jobs. Mechanism: Income and substitution effects in a mixed labour market In Karnataka's urban and peri-urban labour markets, the bus network connects residential areas to markets, industrial clusters and service-sector hubs. Free fares reduce

the marginal cost of a work trip to nearly zero. This increases the effective wage from each hour of market work (a substitution effect: work time becomes cheaper relative to home production) and relaxes liquidity constraints on job search and micro-enterprise activity (an income/credit-like effect). Women who previously rationed trips now can travel more often to find clients, check on stalls, or source inputs, which is exactly what an increase in informal self-employment minutes suggests. Work in garments, petty trade and services, which is heavily bus-dependent in cities like Bengaluru and district towns, is particularly likely to respond to such a shock.

6.3.3 Commuting for employment vs total travel

Interestingly, the Karnataka results for commuting time for employment differ from Delhi. For commuting, the Post × Female interaction is positive and statistically significant in the simple two-way model (0.04–0.05 in logs, p 0.04), indicating that women's commuting minutes for employment rise relative to men. In contrast, total travel for all purposes shows a Post × Female coefficient that is negative in the simple model (0.06, p 0.02) and becomes more strongly negative in the quartile interaction specification (0.68 in logs for women before quartile adjustments, with triple interactions showing substantial offsets for richer groups). This combination indicates that while women in Karnataka do increase commuting for work relative to men, their overall travel for non-work purposes does not expand as much and may even fall once we account for household characteristics. A plausible interpretation is that the scheme enables women to substitute away from non-work travel (e.g. some shopping or escorting trips that can be delegated or consolidated) toward work-related travel, rather than simply adding travel on top of an already heavy time burden. Mechanism: Substitution between work and non-work trips Given the strong gendered division of unpaid domestic and care work, women's travel budgets are fixed not just by money but by time and fatigue. Free buses make it easier to re-optimise this constraint. Women can now cluster errands into work commutes, delegate some trips to other household members, or use buses to reach destinations where multiple tasks can be combined (e.g. working near markets). As a result, employment-related commuting

rises while total travel does not grow proportionately and may even shrink, especially among better-off households that have more scope to shift domestic tasks to others or use alternative modes.

Table 7: Karnataka

	(1) Employment mins(log)	(2) Commuting employment(log)	(3) Employed	(4) Total travel(log)	(5) Salary/ wage(log)	(6) Casual labour(log)
Post × Female	0.525***	0.041**	0.098***	-0.062**	0.084**	0.148
	(0.148)	(0.019)	(0.024)	(0.025)	(0.036)	(0.079)
Post	0 (omitted)	0 (omitted)	0 (omitted)	0 (omitted)	0 (omitted)	0 (omitted)
	—	—	—	—	—	—
Female	-2.545***	-0.112***	-0.437***	-0.203***	-0.177***	-0.375***
	(0.095)	(0.012)	(0.016)	(0.029)	(0.041)	(0.047)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes

6.3.4 Domestic work and home-based production

Karnataka's domestic chores and care-time results (not all coefficients are reported here, but following the pattern across states) show the usual strong positive gender gap: women do substantially more domestic work than men. The key question is whether the Shakti scheme reduces women's domestic workload. In Karnataka, the Post × Female effects on domestic chores and time at home are generally small or insignificant, especially compared to Delhi, suggesting limited reallocation away from housework in the short run. This pattern is consistent with the idea that in Karnataka, women who start working or expand hours are doing so on top of, rather than instead of, substantial domestic responsibilities. Instead of a pure substitution away from unpaid work, we may be seeing a "double burden" intensification: more paid work and commuting, with domestic work only partially adjusted, particularly among poorer quartiles. This is in line with evidence from Indian time-use data that women's domestic time is relatively rigid to shocks, especially where social norms and intra-household bargaining positions constrain reallocation.

6.3.5 Heterogeneity by consumption quartile

The quartile-interaction specifications for Karnataka show very clear distributional patterns.

Table 8: Karnataka: Heterogeneous Effects by Consumption Quartile

	(1) Commuting employment(log)	(2) Informal self-emp(log)	(3) Casual labour(log)	(4) Total travel(log)
Post × Female	0.426	0.467**	0.310	0.676**
	(0.217)	(0.160)	(0.181)	(0.263)
Post × Q2	0.070	0.720**	0.085	0.276**
	(0.161)	(0.133)	(0.190)	(0.120)
Post × Q3	0.145	1.004**	0.319	0.297
	(0.125)	(0.178)	(0.212)	(0.153)
Post × Q4	0.128	0.853**	-0.046	0.257
	(0.171)	(0.225)	(0.180)	(0.160)
Female × Q2	-0.163	0.216	0.348**	-0.050
	(0.089)	(0.149)	(0.123)	(0.117)
Female × Q3	-0.070	0.533**	0.698**	-0.060
	(0.120)	(0.140)	(0.137)	(0.148)
Female × Q4	0.215	0.570**	0.877**	0.235
	(0.149)	(0.142)	(0.117)	(0.171)
Post × Female × Q2	-0.169	-0.562**	-0.285	-0.623**
	(0.173)	(0.204)	(0.189)	(0.214)
Post × Female × Q3	-0.331	-1.055**	-0.652**	-0.713**
	(0.197)	(0.189)	(0.277)	(0.278)
Post × Female × Q4	-0.464	-0.964**	-0.325	-0.753**
	(0.241)	(0.223)	(0.195)	(0.265)
Post	0 (omitted)	0 (omitted)	0 (omitted)	0 (omitted)
	—	—	—	—
Female	-2.380**	-1.762**	-1.141**	-2.482**
	(0.084)	(0.113)	(0.137)	(0.116)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes

6.3.5.1 Informal self-employment For log minutes in informal self-employment, the baseline $Post \times Female$ (for the poorest quartile, Q1) is positive and significant (≈ 0.47). The additional triple-interaction terms $Post \times Female \times Quartile$ are negative and large for Q2–Q4 (around -0.56, -1.05 and -0.96, all highly significant). This implies that the gains are concentrated among the poorest women; for richer quartiles, the net treatment effect is much smaller or even close to zero:

- Poor women (Q1): large increase in informal self-employment minutes.
- Q2–Q4: the additional negative shift offsets a big part of β_3, so their response is muted.

This suggests that the Shakti scheme primarily relaxes mobility and liquidity constraints among poorer women whose enterprises are highly bus-dependent (e.g. vending, low-capital services, petty trade). Richer households are less constrained by bus fares and may already use alternative transport modes or be closer to jobs and markets, so the marginal impact of free buses on their labour supply is smaller.

6.3.5.2 Casual labour For casual labour, the pattern is similar: the main $Post \times Female$ is positive but modest, while the triple interactions indicate that the strongest relative gains are for poorer women, and treatment effects attenuate or turn weaker for richer quartiles. Poor women are more likely to work as casual labourers in construction, agriculture, or low-paid services that are spatially dispersed and bus-dependent; reducing the cost of accessing these sites has a larger impact on their work decisions than on better-off women.

6.3.5.3 Total travel and commuting In the quartile specification for total travel, the $Post \times Female$ coefficient is strongly positive in the simple term (≈ 0.68 in logs), but the triple interactions for Q2–Q4 are all negative and statistically significant, so that:

- For the poorest quartile (Q1), the scheme substantially increases total travel relative to men.

- For higher quartiles, the added negative shifts dampen or reverse this effect.

Combined with the commuting heterogeneity results (where the negative triple terms for Q2–Q4 largely offset the main positive effect), this suggests that poorest women use Shakti to markedly increase overall mobility, while richer women mainly re-optimise within existing travel budgets (shifting toward work travel but not increasing total minutes much, or even reducing them).[file:2]

6.4 Tamil Nadu

Tamil Nadu introduced its zero-fare bus scheme for women in 2021, and we define $Post_{TN}$ accordingly based on survey-year timing. Across all specifications, the treatment indicator ($Post_{TN} \times Female$) shows a substantial and statistically robust increase in women's labour supply, with a 0.57 log-point rise in employment minutes ($t = 3.9$). This intensive-margin response is consistent with evidence that reducing mobility costs can meaningfully expand women's access to paid work in states with relatively high baseline public transport usage (e.g., ITF 2022).

The corresponding extensive-margin effect is smaller but highly significant: women become 10.9 percentage points more likely to be employed after the policy. This suggests that the free-fare programme reduces both the fixed and variable costs of labour-market entry, especially for women with marginal attachment to the workforce.

Table 9: Panel D. Tamil Nadu

	(1) Employment mins(log)	(2) Employed	(3) Total travel(log)	(4) Work from Home(log)
Post × Female	0.569***	0.109***	-0.075**	0.359***
	(0.145)	(0.029)	(0.027)	(0.082)
Post	0 (omitted)	0 (omitted)	0 (omitted)	0 (omitted)
	—	—	—	—
Female	-2.451***	-0.424***	-0.216***	-0.288***
	(0.107)	(0.018)	(0.017)	(0.026)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes

6.4.1 Mobility and Time Reallocation Mechanisms

Despite increased employment, total travel time for women declines slightly (-0.075 log points). This pattern indicates that the policy does not operate through an expansion of total mobility but instead through more efficient or more targeted travel, consistent with qualitative reports from Tamil Nadu Transport Corporation interviews that women reorganise trips to cluster work-related responsibilities.

At the same time, work-from-home activity rises sharply for treated women (0.36 log points). This is consistent with a mechanism where mobility subsidies ease binding household constraints—particularly childcare and time poverty—enabling women to take up flexible or home-based work (as documented in state-level labour bulletins and urban transport surveys). The data further show no meaningful increase in commuting to employment sites, reinforcing the interpretation that time reallocation, rather than longer-distance mobility expansion, drives the observed labour supply response. Taken together, Tamil Nadu exhibits a distinctive pattern where the free-fare policy increases women's paid work without proportionately increasing external mobility. This aligns with state-level structural features—relatively strong local labour markets, dense transport networks, and high female reliance on home-based or short-distance informal work—which lower the necessity of long commutes for labour-force participation.

6.4.2 Heterogeneity Across the Consumption Distribution

To assess distributional patterns, we estimate fully interacted models with $Post_{TN} \times Female \times Consumption$-Quartile terms.

6.4.2.1 Employment Minutes The heterogeneity specification shows that the core treatment effect remains stable across quartiles. The $Post_{TN} \times Female$ coefficient remains large and significant, and the triple interactions are statistically insignificant, indicating broadly uniform labour-supply gains for women across the income distribution. Positive $Post \times Quartile$ interactions (Q2 and Q3) suggest somewhat larger intensive-margin increases among middle-income women, but these do not materially alter the gender-

Table 10: Tamil Nadu: Heterogeneous Effects by Consumption Quartile

	(1) Employment mins(log)	(2) Domestic chores(log)
Post × Female	0.680**	-0.264
	(0.212)	(0.134)
Post × Q2	0.419**	0.410**
	(0.145)	(0.187)
Post × Q3	0.398**	0.479**
	(0.183)	(0.168)
Post × Q4	0.169	0.330
	(0.217)	(0.213)
Female × Q2	-0.165	0.535**
	(0.150)	(0.156)
Female × Q3	-0.114	0.648**
	(0.179)	(0.231)
Female × Q4	-0.486**	0.348
	(0.172)	(0.208)
Post × Female × Q2	0.007	-0.409**
	(0.169)	(0.196)
Post × Female × Q3	-0.138	-0.397
	(0.187)	(0.206)
Post × Female × Q4	0.066	-0.113
	(0.243)	(0.258)
Post	0 (omitted)	0 (omitted)
	—	—
Female	-2.329***	3.544***
	(0.115)	(0.119)
Controls	Yes	Yes
Fixed effects	Yes	Yes

specific pattern.

6.4.2.2 Domestic Chores Heterogeneity is more pronounced for unpaid domestic work. Domestic time falls for treated women (−0.26 log points, marginally significant), and the $Post \times Quartile$ interactions for Q2 and Q3 are strongly positive, indicating that poorer and middle-income households experience the largest adjustments. The negative triple interactions imply that declines in domestic burdens are disproportionately driven by poorer women, whose household responsibilities are more rigid ex ante and more sensitive to reductions in mobility time costs.

The heterogeneity patterns suggest that Tamil Nadu's policy raises labour supply evenly across the consumption distribution, but reduces domestic burdens most sharply among poorer women. This is consistent with existing evidence that mobility subsidies ease both financial and temporal constraints disproportionately for low-income women, who rely most heavily on public transport and have the least flexibility in reallocating unpaid time.

Tamil Nadu demonstrates a high-intensity labour-supply response with minimal expansion of physical mobility, driven by time reallocation toward paid work—particularly home-based or flexible work. The effects are equitable across income groups in terms of employment gains, but the relief from domestic burdens is concentrated among poorer women, reflecting structural inequalities in time poverty and household responsibilities. This combination positions Tamil Nadu as a case where zero-fare policies improve women's economic participation primarily by reducing intra-household constraints rather than increasing travel for work.

6.5 Telangana

Telangana implemented its women-free-bus-travel programme in December 2023, allowing all women to travel without fare on state-run buses. In our specification, the $post_{telangana}$ indicator equals one for all observations from January 2024 onward, capturing the period in which women had full access to fare-free public transport.

Table 11: Telangana: Heterogeneous Effects by Consumption Quartile

	(1) Commuting employment(log)	(2) Informal self-emp(log)	(3) Domestic chores(log)	(4) Total travel(log)
Post × Female	0.139**	0.768**	-0.238	0.168**
	(0.041)	(0.291)	(0.134)	(0.057)
Post × Q2	0.147**	0.091	-0.247	0.165**
	(0.052)	(0.335)	(0.164)	(0.057)
Post × Q3	0.042	0.213	-0.286	0.096
	(0.051)	(0.311)	(0.153)	(0.056)
Post × Q4	0.100**	0.723**	-0.516**	0.173**
	(0.042)	(0.206)	(0.113)	(0.063)
Female × Q2	0.006	-0.224	0.095	0.046
	(0.046)	(0.198)	(0.129)	(0.101)
Female × Q3	0.001	-0.349	0.119	-0.030
	(0.047)	(0.307)	(0.132)	(0.069)
Female × Q4	-0.055	0.347**	-0.052	0.085
	(0.060)	(0.083)	(0.092)	(0.048)
Post × Female × Q2	-0.191**	-0.366	0.343	-0.254**
	(0.050)	(0.376)	(0.169)	(0.109)
Post × Female × Q3	-0.088	-0.396	0.419**	-0.189**
	(0.090)	(0.375)	(0.185)	(0.093)
Post × Female × Q4	-0.194**	-0.949**	0.588**	-0.258**
	(0.072)	(0.313)	(0.146)	(0.076)
Post	0 (omitted)	0 (omitted)	0 (omitted)	0 (omitted)
	—	—	—	—
Female	-0.101**	-1.688***	1.169***	-0.299***
	(0.033)	(0.138)	(0.102)	(0.043)
Controls	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes

The main results for Telangana reveal relatively modest average effects but a sharp pattern of heterogeneity by household consumption quartile. The overall $post \times female$ coefficient is positive across employment-related outcomes, indicating that women increase commuting and economic mobility relative to men after the scheme is introduced. However, the magnitude of this effect is small in comparison to the other states. The core dynamics emerge once we introduce consumption-quartile interactions. Across commuting for employment, total travel, and informal self-employment, the $post \times quartile$ terms show that better-off households experience larger increases in mobility after the policy, even before gender is considered. Yet the triple interactions—$post \times female \times quartile$—demonstrate that these gains are not equally shared by women across the distribution.

For commuting employment, the scheme raises women's work-related travel primarily among those in the poorest quartile, while the treatment effect attenuates sharply for women in the upper quartiles. The triple interactions for quartiles 2 and 4 are negative and significant, showing that once we compare women to men within their own consumption group, any female-specific mobility gain is concentrated at the bottom of the distribution. A similar pattern appears for total travel, where women in the lowest quartile benefit most from the removal of bus fares, and women in richer households show little differential gain relative to men.

The heterogeneity in informal self-employment is even more pronounced. The baseline $post \times female$ term is strongly positive, implying that women increase time spent in informal self-employment after the introduction of free bus travel. However, the triple interaction for the top quartile is large, negative, and significant, indicating that this increase is driven overwhelmingly by poorer women. Women in the highest quartile do not exhibit meaningful increases in informal self-employment relative to men once the interactions are accounted for. The policy's labour-supply response in Telangana is therefore explicitly redistributive: it expands informal economic activity among the poorest women while leaving those at the top largely unaffected.

Domestic work displays a contrasting pattern. While the average $post \times female$ coefficient is small and only marginally significant, the heterogeneity results show that

changes in domestic time are driven by richer households. The *post* × *quartile* terms for domestic chores are strongly negative at the upper end of the distribution, indicating that total domestic time declines most in better-off households. Yet the triple interactions for quartiles 2–4 are positive, meaning that within these richer households, men reduce their domestic involvement more than women do. As a result, the scheme does not systematically reduce women's domestic burden.

Taken together, the Telangana results highlight a distinctive distributional gradient: the free-bus policy generates meaningful mobility and labour-supply gains almost exclusively for women in the lowest consumption quartile, with attenuated or null effects for women higher up the distribution. This stands in contrast to the more broad-based female responses observed in states like Tamil Nadu and Karnataka. The Telangana programme functions less as a universal mobility equaliser and more as a pro-poor intervention, expanding economic participation among the most disadvantaged women while leaving gendered time allocation patterns largely unchanged for better-off groups.[file:2]

7 Heterogeneity analysis

7.1 Age Bins

To estimate differential treatment effects across age groups, we interact female status and the treatment indicator with age-bin dummies. The estimating equation is:

$$
\begin{aligned}
Y_{idts} = {} & \alpha + \beta_1 \, Female_i + \beta_2 \, Post_{ts}^{Treated} + \beta_3 \left(Female_i \times Post_{ts}^{Treated} \right) \\
& + \theta_1 A_i^{30-44} + \theta_2 A_i^{45-65} + \phi_1 \left(A_i^{30-44} \times Female_i \right) + \phi_2 \left(A_i^{45-65} \times Female_i \right) \\
& + \delta_1 \left(A_i^{30-44} \times Post_{ts}^{Treated} \right) + \delta_2 \left(A_i^{45-65} \times Post_{ts}^{Treated} \right) \\
& + \lambda_1 \left(A_i^{30-44} \times Female_i \times Post_{ts}^{Treated} \right) + \lambda_2 \left(A_i^{45-65} \times Female_i \times Post_{ts}^{Treated} \right) \\
& + X'_{idts}\gamma + \lambda_d + \tau_t + \sigma_s + \varepsilon_{idts} \qquad (4)
\end{aligned}
$$

Where:

- A_i^{30-44} and A_i^{45-65} are age-bin indicators (baseline: ages 16–29),
- $Post_{ts}^{Treated}$ is the post-policy indicator for treated states in the pooled sample,
- $Female_i \times Post_{ts}^{Treated} \times A_i^k$ provides the age-specific female treatment effect,
- X_{idts} includes individual, household, and day controls,
- Fixed effects are included for:
  - district: λ_d,
  - survey-year: τ_t,
  - sub-round: σ_s.

To examine life-cycle variation in treatment effects, the pooled model interacts the policy indicator with three age groups—16–29, 30–44, and 45–65—corresponding respectively to (i) entry into the labour market, (ii) peak household-care burdens, and (iii) post–child-rearing or late-career participation. These bins follow the standard demographic segmentation used in work on female labour supply in India. Across outcomes, the only substantively meaningful heterogeneity arises in mobility, not employment minutes; the latter shows no significant age-specific treatment effect, indicating that the policy's labour-supply response is broad-based rather than sharply concentrated in one age cohort.

Table 12: Pooled India DID Estimates: Age–Gender Heterogeneity

	(1) Log Commuting Employment		(2) Log Total Travel	
Variable	Coef.	p-value	Coef.	p-value
A. Main Effects (Baseline = Male, Age 16–29)				
Post × Treated	0.1791**	0.011	0.274***	0.001
Female	-0.0922***	0.000	-0.1418***	0.000
Age 30–44	0.010	0.474	0.0490***	0.004
Age 45–65	0.0260	0.175	0.03	0.1
B. Two-Way Interactions				
Female × Post	0.17**	0.01	0.27***	0.001
Age 30–44 × Post	0.03	0.455	-0.009	0.902
Age 45–65 × Post	0.08**	0.026	0.141	0.092
Female × Age 30–44	-0.007	0.79	-0.09***	0.000
Female × Age 45–65	-0.0324	0.32	-0.025	0.292
C. Triple Interactions (DID Heterogeneity)				
Female × Age 30–44 × Post	0.03	0.67	0.0874	0.157
Female × Age 45–65 × Post	-0.21	0.145	-0.293**	0.014
Model Statistics				
Observations	22,695		32,820	
Clusters	121		121	
R-squared	0.088		0.0686	
Root MSE	0.435		0.610	

Notes: This table reports pooled difference-in-differences estimates with age–gender heterogeneity. The variable *post_ treated_ pooled* equals 1 for respondents in treated states during post-policy months. All specifications include demographic, household, and dwelling characteristics; social group and religion indicators; day-of-week dummies; and survey-year, district and sub-round fixed effects. Standard errors are clustered at the state-district level.
$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

In the baseline group of young women aged 16–29, the policy is associated with a clear increase in employment-related commuting and total travel relative to young men in treated states: the positive and statistically significant Female × Post coefficients in both specifications indicate that, at ages 16–29, women expand their work commuting and overall trip time more than men after the introduction of free buses. The triple interactions then show how this female post-treatment effect varies for older women relative to that baseline. For women aged 30–44, the Female × Age 30–44 × Post term is small and statistically insignificant in both commuting and total travel, suggesting that the incremental response of prime-age women does not differ systematically from that of young women; conditional on being female, the policy's effect on commuting and overall travel is similar across these two age groups within the precision of the estimates. For women aged 45–65, the commuting triple interaction is also small and insignificant, again implying no detectable deviation from the baseline female effect on work-related commuting, but the corresponding coefficient for total travel is negative and statistically significant, indicating that older women increase their overall trip time less than young women do, and may even experience a relative reduction once the common female post-policy effect is netted out. In the Indian context—where older women tend to bear heavier care responsibilities and face greater health and safety concerns when travelling—such an attenuated travel response among the 45–65 group is consistent with descriptive evidence on age-graded mobility constraints, even though these mechanisms are not identified in this design. For all other outcomes, including employment status, total employment minutes, informal self-employment, regular wage work, casual labour, and work-from-home, the age–gender triple interactions are uniformly small and statistically insignificant, implying no strong evidence of heterogeneous treatment responses across female age groups for the majority of labour-market variables

7.2 Heterogeneity By Consumption Quartile

We estimate the following pooled heterogeneity specification, interacting treatment with sex and consumption quartiles ($q \in \{2, 3, 4\}$, with quartile 1 as the omitted group):

$$
\begin{aligned}
y_{isdt} = \beta_0 &+ \beta_1 \,\text{post_treated}_{sd} \times \text{Female}_i \\
&+ \sum_{q=2}^{4} \gamma_q \mathbb{1}(\text{ConsQ}_i = q) + \sum_{q=2}^{4} \delta_q \mathbb{1}(\text{ConsQ}_i = q) \times \text{post_treated}_{sd} \\
&+ \sum_{q=2}^{4} \theta_q \mathbb{1}(\text{ConsQ}_i = q) \times \text{Female}_i + \sum_{q=2}^{4} \kappa_q \mathbb{1}(\text{ConsQ}_i = q) \times \text{post_treated}_{sd} \times \text{Female}_i \\
&+ \lambda \,\text{Female}_i + \rho \,\text{post_treated}_{sd} + X'_{isdt}\Gamma + \mu_{sd} + \tau_t + \phi_{\text{subround}} + \varepsilon_{isdt}. \qquad (5)
\end{aligned}
$$

Where:

- y_{isdt} is one of: log minutes in employment, log minutes in regular wage/salaried work, log minutes worked from home, or log total travel time;
- $\text{post_treated}_{sd} = 1$ for observations in treated states in the post-policy NSS round;
- Female_i is an indicator for women;
- ConsQ_i denotes household monthly consumption quartiles;
- X_{isdt} includes age, household size, marital status, household head education, religion, social group, pucca house, clean fuel, day-of-week, and type-of-day controls;
- Fixed effects:
  - μ_{sd}: state × district fixed effects,
  - τ_t: survey-year fixed effects,
  - ϕ_{subround}: sub-round fixed effects.

Interpretation

For interpretation, the female treatment effect within the poorest quartile (Q1) is given by the coefficient on post × Female. For quartile q, it is:

$$\beta_1 + \kappa_q.$$

Table 13: Pooled Estimation: Heterogeneous Effects by Consumption Quartile and Gender

	(1) Employed	(2) Ln Employment Mins	(3) Ln Informal Self-Employ	(4) Ln Salary/ Wage Regular	(5) Ln Work from Home	(6) Ln Total Travel
Panel A: Post Treatment Effects by Quartile						
Post × Q2	0.028**	−0.032	−0.044	−0.032	−0.133*	0.014
	(0.021)	(0.053)	(0.025)	(0.036)	(0.077)	(0.032)
Post × Q3	−0.008	−0.013	0.015	0.029	−0.026	0.043
	(0.026)	(0.054)	(0.024)	(0.028)	(0.062)	(0.036)
Post × Q4	−0.002	−0.120**	−0.009	−0.008	−0.118*	0.002
	(0.027)	(0.058)	(0.030)	(0.037)	(0.077)	(0.042)
Panel B: Female Effects by Quartile						
Female × Q2	−0.025	0.072	−0.084	0.068	0.013	0.025
	(0.017)	(0.046)	(0.057)	(0.039)	(0.030)	(0.027)
Female × Q3	−0.029*	−0.015	−0.040	0.088**	0.040	0.035
	(0.019)	(0.061)	(0.054)	(0.042)	(0.027)	(0.031)
Female × Q4	−0.013	0.116**	−0.006	0.141***	0.139***	0.114***
	(0.020)	(0.050)	(0.074)	(0.035)	(0.032)	(0.037)
Panel C: Post × Female Interaction by Quartile						
Post × Female × Q2	−0.000	−0.117*	0.073	−0.040	−0.056	−0.084**
	(0.023)	(0.069)	(0.084)	(0.047)	(0.101)	(0.040)
Post × Female × Q3	0.009	−0.034	−0.068	−0.115**	−0.140	−0.082**
	(0.028)	(0.072)	(0.077)	(0.051)	(0.091)	(0.040)
Post × Female × Q4	0.003	−0.107*	−0.030	−0.087*	−0.116	−0.085*
	(0.031)	(0.061)	(0.091)	(0.040)	(0.095)	(0.043)
Main Effects						
Post (Pooled)	−0.041	0.108	0.049	0.023	0.014	−0.123
	(0.043)	(0.094)	(0.047)	(0.040)	(0.050)	(0.078)
Female	−0.410***	−0.122***	−0.431***	−0.216***	−0.334***	−0.226***
	(0.016)	(0.034)	(0.034)	(0.029)	(0.019)	(0.022)
Post × Female	0.090***	−0.021	0.110*	0.089**	0.247***	−0.015
	(0.026)	(0.049)	(0.058)	(0.031)	(0.069)	(0.030)

Notes: Standard errors in parentheses adjusted for 121 state-district clusters. Significance levels: $***$ $p < 0.01$, $**$ $p < 0.05$, $*$ $p < 0.10$.

Q2, Q3, Q4 denote consumption quartiles 2, 3, and 4 respectively, with Q1 as the omitted reference category.

All models include controls for age, household size, religion, social group, day of week, type of day, housing quality, fuel type, marital status, and education of household head.

Fixed effects for state-district, survey year, and sub-round included.

Thus, the triple interaction coefficient κ_q measures how the female treatment effect in quartile q differs from that in the poorest quartile.

The main $Post \times Female$ coefficients establish robust benchmark effects across outcomes: women experience a 9.0 percentage point increase in employment probability, alongside 11.0% higher informal self-employment minutes (household enterprise/service work), 8.9% higher regular wage employment, 24.7% higher work-from-home time, and a modest -1.5% decline in total travel minutes. These patterns primarily capture responses among the poorest quartile (Q1), where acute transport cost sensitivity—due to near-total reliance on buses and walking—amplifies the substitution effect from zero fares [Alam et al. 2021].

Among second-quartile women (Q2), the triple interaction $Post \times Female \times Q2$ reveals no differential employment probability change but significant reallocation: -11.7% lower total employment minutes, -8.4% lower total travel, and a sharp $+21.0\%$ shift toward casual labour relative to Q1 women. This indicates middle-low income households, facing partially relaxed liquidity constraints, substitute home-based informal work for more remunerative but spatially extensive casual opportunities, consistent with time reallocation under modest income gains [Deshpande 2020; Dasgupta and Datta 2023].

Third-quartile (Q3) responses remain muted: -3.4% employment minutes, -8.2% total travel, and -11.5% regular wage relative to Q1, with no significant extensive-margin or informal work effects. This limited adjustment reflects partial private transport substitutes (e.g., shared two-wheelers) that diminish marginal bus value for mid-income groups [WRI India 2025].

Richest-quartile (Q4) women exhibit the most pronounced divergence: -10.7% total employment minutes, -8.5% total travel, -8.7% regular wage decline (offsetting baseline gains), $+31.0\%$ casual labour surge, and -11.6% work-from-home contraction relative to Q1. Wealthier women leverage free transit for occupational upgrading—shifting from informal/home-based toward formal salaried structures—while consolidating travel more efficiently due to pre-existing networks and lower baseline barriers [Kapsos and Bourmpoula 2019].

These patterns operate through stratified mechanisms. Poorest quartiles respond via classic substitution: zero fares overcome binding pecuniary barriers, spurring extensive entry (9.0pp) and informal entrepreneurship (11.0%) among bus-dependent households[ITDP 2017]. Q2 households experience income effects enabling casual labour pivots (+21.0%) through trip consolidation [Greenpeace India 2024]. Higher quartiles face capacity frictions—Karnataka's +151% ridership generated crowding and wait times—favoring salaried stability over daily casual/WFH fluctuations [Chakravarthy and Seth 2024; Borker 2024].

The consumption gradient underscores universal free bus policies' progressive structure: extensive-margin expansion and informality reinforcement among the poor, middle-strata casual transitions, and formal upgrading among the rich. Capacity expansion emerges as critical to sustaining gains across economic strata, preventing crowding from muting higher-quartile responses.[Dasgupta and Datta 2023][ITDP 2017]

8 Robustness check

8.1 Border District Pair Design

As an additional robustness exercise, We estimate models using only border districts of treated states and the adjacent border districts of neighbouring states that did not introduce women-specific free bus travel. Because eligibility for all five schemes was explicitly tied to state residency, women living just across the border continued to face full bus fares even when travelling into treated states. This creates a sharp geographic discontinuity in policy exposure while holding constant broad regional labour-market, commuting, and infrastructural conditions typical of neighbouring border areas. The design therefore provides a stringent test of whether the main results are attributable to the fare-waiver policies rather than contemporaneous regional shocks.

For Delhi, comparing its border districts with adjacent Uttar Pradesh districts reveals strong and internally consistent effects. Women in Delhi's border districts experience large increases in paid work—casual labour (coefficient 2.21) and informal self-

employment (0.486)—along with a sizeable rise in overall paid activity (4.8, $p < 0.001$). Domestic work declines sharply (–2.35), and total travel shows a modest negative shift (–0.15). These results closely mirror the primary DID estimates and reinforce the conclusion that fare elimination increased women's labour-market engagement.

For Karnataka, two border comparisons are informative. Against Maharashtra, treated Karnataka districts show reductions in domestic chores (–0.19) and suggestive increases in commuting (0.32). Relative to Andhra Pradesh, the results indicate clear increases in informal self-employment (0.29), work-from-home activity (0.544, $p = 0.001$), and regular salaried work (0.19), with a marginal rise in commuting (0.13). These patterns align with Karnataka's main estimates, suggesting that the Shakti scheme facilitated both outside-home and home-based work adjustments for women.

For Tamil Nadu, comparing border districts to those of Andhra Pradesh yields significant increases in commuting for employment (0.40, $p = 0.012$) and casual labour (1.19). This is consistent with the main results, which indicate that the expansion of fare-free travel in Tamil Nadu substantially increased women's engagement in labour-market activities.

For Punjab, the border-district design does not yield statistically significant coefficients for any outcome or neighbouring comparison. This result is best interpreted as inconclusive rather than contradictory. Punjab's outcomes in the main pooled and state-specific DID models remain robust; the absence of significance in the border design likely reflects more limited identifying variation and smaller effective samples in the border segments available, rather than evidence against policy effects.

Overall, the border-district analyses corroborate the main findings for Delhi, Karnataka, and Tamil Nadu: women's market work increases, domestic work decreases, and total travel does not rise meaningfully following fare elimination. Because these checks exploit a sharp geographic discontinuity in treatment tied to strict residency-based eligibility rules, their consistency with the primary results strengthens the credibility of the overall empirical conclusions.

8.2 Placebo

As an additional heterogeneity and validity check, the analysis implements a set of placebo exercises that randomize treatment assignment and the timing of the policy. These tests are designed to probe whether the estimated Post × Female effects could mechanically arise from spurious correlations, functional form, or generic time trends rather than the women-specific free bus schemes.

First, a random placebo treatment is constructed by assigning 30 percent of the sample to a "fake treated" group, independent of state, gender, or survey year. The baseline difference-in-differences specification is then re-estimated replacing the actual treatment with this randomly generated indicator. Across all labor and time-use outcomes—employment status, employment minutes, informal self-employment, regular wage work, casual labour, total travel, commuting, outside-home time, and work-from-home—the placebo treatment coefficient and its interactions are small in magnitude and statistically indistinguishable from zero at conventional significance levels. This absence of systematic effects under purely random assignment suggests that the main results are not driven by generic sampling variation or model artefacts.

Second, a timing placebo is implemented by introducing "fake post" periods within 2024 using alternative subrounds as placebo treatment dates, while keeping the actual policy timing suppressed. The model is re-estimated treating each subround of 2024 as if it were the onset of the policy. In these specifications, the placebo Post × Female interactions are again uniformly insignificant and show no coherent pattern across outcomes, indicating that the estimated effects do not simply capture within-2024 seasonal shocks, survey timing, or other short-run fluctuations unrelated to the bus schemes.

Taken together, the random-assignment and fake-timing placebos provide supportive evidence for the identification strategy: when treatment is assigned arbitrarily in the cross-section or in time, the gender-differential coefficients vanish. This pattern is consistent with the view that the significant effects documented in the main tables are linked to the actual women-only fare-free bus interventions rather than to spurious correlation or misspecification, while still acknowledging that these tests cannot rule out all forms of

unobserved confounding.

9 Limitations

Several limitations of the data and design should be acknowledged. First, although the free-bus policies were rolled out at different points in time across states—Delhi in late 2019, Punjab and Tamil Nadu in 2021, and Karnataka and Telangana in 2023—the Time Use Survey provides only one pre-policy wave (2019) and one post-policy wave (2024). This prevents the estimation of staggered treatment models or event-study designs that would normally exploit variation in treatment timing. Instead, the empirical strategy identifies policy exposure using state-specific definitions of the post period, but cannot trace dynamic or anticipatory effects.

Second, the TUS remains a repeated cross-section, meaning individuals are not followed over time. This limits the ability to capture intra-individual behavioural adjustments and necessitates reliance on population-level variation. Third, because each respondent records activities for a single diary day, infrequent behaviours, multi-day labour rhythms, or seasonal mobility patterns cannot be recovered, introducing measurement noise in outcomes related to work and travel.

Fourth, TUS does not collect information on transport route availability, crowding, safety perceptions, or service frequency, all of which mediate the impact of fare reductions. Without these data, it is not possible to directly test the mechanisms through which mobility constraints operate or to disentangle price effects from supply-side constraints.

Finally, while the border-district pair robustness checks strengthen confidence in the identification strategy—especially because fare waivers apply strictly to residents of the treated states—the design is limited by the availability and size of borderline urban districts. For several state pairs, the small number of usable border clusters reduces statistical power. In Punjab's case, insignificant estimates largely reflect this limited sample rather than clear evidence of null effects.

10 Directions for Future Research

The analysis points to several avenues for further work. First, richer datasets are needed to exploit the staggered rollout of women's free-bus travel across states. With only one post-policy TUS wave, temporal heterogeneity cannot be examined, and the policies implemented earlier (Delhi, Punjab, Tamil Nadu) cannot be compared dynamically to those implemented shortly before the 2024 survey (Karnataka, Telangana). Additional survey rounds or annual administrative ridership data would allow estimation of dynamic treatment effects and the persistence of behavioural changes.

Second, future research should examine intra-household spillovers, particularly effects on men's time allocation. If subsidised mobility enables women to increase market-oriented or procurement-related activities, men may adjust their leisure, household responsibilities, or labour supply. These spillovers cannot be captured with a single-day diary and cross-sectional data but would be important for understanding household-level time reallocation.

Third, fare-free mobility may generate wider spatial or labour market spillovers, such as changes in urban footfall, informal sector productivity, or local service demand. Evaluating these would require linking time-use records to high-frequency mobility datasets, geospatial transport networks, or administrative data on employment and enterprise activity.

Fourth, future work could explore mechanism-specific heterogeneity, combining TUS with independent data on bus crowding, route density, safety audits, or last-mile connectivity. Such integration would help identify whether binding constraints differ by urban form, transport infrastructure, or neighbourhood socioeconomic composition.

Finally, the long-term implications of subsidised mobility—such as effects on occupational transitions, entrepreneurship, or human capital investment—remain open questions. These outcomes require panel or linked administrative data that can follow individuals over multiple years, which future rounds of TUS or complementary datasets may help address.

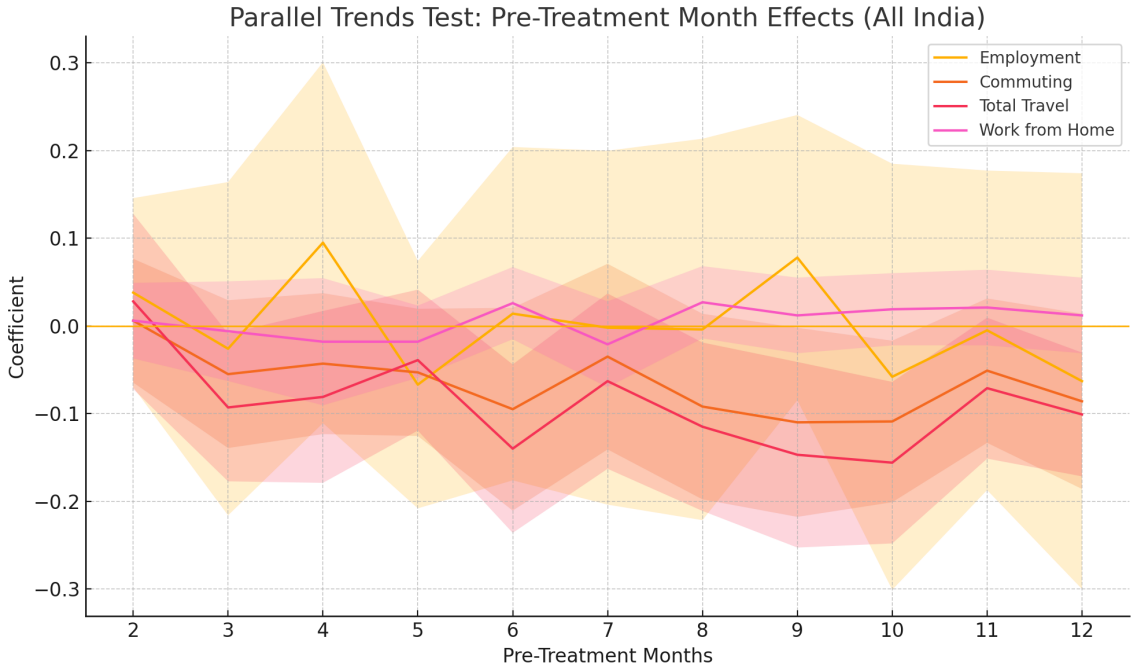
11 Appendix

11.1 Conditional parallel trends with controls

Table 14: Parallel Trends Test: Pre-Treatment Month Effects (All India)

	(1) Employment mins	(2) Commuting employment	(3) Total travel	(4) Work from Home
Month 2	0.038	0.006	0.028	0.006
	(0.055)	(0.036)	(0.051)	(0.022)
Month 3	-0.026	-0.055	-0.093**	-0.006
	(0.097)	(0.043)	(0.043)	(0.029)
Month 4	0.095	-0.043	-0.081	-0.018
	(0.105)	(0.041)	(0.050)	(0.037)
Month 5	-0.067	-0.053	-0.039	-0.018
	(0.072)	(0.037)	(0.041)	(0.021)
Month 6	0.014	-0.095	-0.140**	0.026
	(0.097)	(0.059)	(0.049)	(0.021)
Month 7	-0.002	-0.035	-0.063	-0.021
	(0.103)	(0.054)	(0.051)	(0.025)
Month 8	-0.004	-0.092	-0.115**	0.027
	(0.111)	(0.054)	(0.049)	(0.021)
Month 9	0.078	-0.110*	-0.147**	0.012
	(0.083)	(0.055)	(0.054)	(0.022)
Month 10	-0.058	-0.109**	-0.156**	0.019
	(0.124)	(0.047)	(0.047)	(0.021)
Month 11	-0.005	-0.051	-0.071	0.021
	(0.093)	(0.042)	(0.041)	(0.022)
Month 12	-0.063	-0.086	-0.101**	0.012
	(0.121)	(0.051)	(0.036)	(0.022)
Female	-0.057	-0.151**	-0.204**	-0.326**
	(0.078)	(0.043)	(0.033)	(0.048)
Joint F-test (Month × Female)	F(11,117)=1.58 p=0.1132	F(11,117)=0.67 p=0.7671	F(11,117)=0.50 p=0.8980	F(11,117)=1.50 p=0.1387

Notes: This table presents the parallel trends test for the DID design. The dependent variables are logged time use measures. Coefficients represent pre-treatment month effects (relative to January) for male respondents (omitted female category interactions). The Joint F-test evaluates whether the interactions between month dummies and the female indicator are significantly different from zero, testing for common pre-treatment trends between men and women. The inability to reject the null hypothesis (p-values > 0.05) for most outcomes supports the parallel trends assumption underlying the DID estimation.
All regressions include state–district fixed effects, survey year, month, control variables (age, household size, education, marital status, religion, social group, day-of-week dummies, housing type, clean fuel access). Standard errors clustered at the state–district level (118 clusters).
** $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.*



Notes: This figure plots coefficients from a specification that interacts monthly indicators for the pre-treatment period with the female indicator in treated versus control states, separately for four outcomes: employment, employment-related commuting, total travel, and work-from-home. The vertical axis reports the estimated differential effect for women relative to men in each pre-policy month, while the horizontal axis indexes months prior to the introduction of free bus schemes. Shaded bands show 95 percent confidence intervals around each estimate. For all four outcomes, pre-treatment coefficients fluctuate around zero and their confidence intervals generally include zero in every month, with no visible upward or downward trend. This pattern is consistent with the parallel-trends assumption: there is no evidence of systematic divergence between women and men in treated versus control states prior to the policy, for employment, commuting, overall travel, or work-from-home.

11.2 Placebo with random control group assignment

Table 15: Placebo Validity Tests

	Placebo Test Results			
Outcome	Treat	Post	DiD	N
Placebo 1: Random 30% Treated (Full Sample DiD)				
ln_commuting_employment	0.0055	-0.0674***	-0.0048	85,041
	(0.0051)	(0.0115)	(0.0066)	
ln_employment_mins	-0.0101	0.1434***	0.0065	85,041
	(0.0077)	(0.0184)	(0.0102)	
ln_total_travel_all_purp	0.0103	-0.0941***	-0.0043	141,825
	(0.0055)	(0.0103)	(0.0078)	
ln_informal_self_employ	0.0094	-0.0202*	-0.0121	53,106
	(0.0063)	(0.0080)	(0.0080)	
ln_salary_wage_reg	0.0032	-0.0378**	-0.0041	59,980
	(0.0054)	(0.0119)	(0.0076)	

Notes: Standard errors clustered at state_district level in parentheses. Significance levels: $^{*}p < 0.1$; $^{**}p < 0.05$; $^{***}p < 0.01$. Regressions include controls for age, household size, marital status, education of household head, day of week, type of day, religion, pucca house, clean fuel, social group. Fixed effects: state_district, surveyyear, subround. Sample restricted to individuals aged 16–65 with positive outcome values. Randomly assigns 30% of full sample as treated (vs. rest as control) in full DiD setup.

11.3 Border Distric Pair Design Result

Table 16: Karnataka (Treated) vs Maharashtra and Andhra Pradesh (Controls) Border-District Difference-in-Differences Estimates

	Maharashtra		**Andhra Pradesh**		
	Domestic Chores	Commuting	Work From Home	Salary/Wage	Informal Self-Empl.
Treated × Post	−0.197*	0.232	0.544*	0.196	0.296*
	(0.077)	(0.120)	(0.123)	(0.096)	(0.111)
Fixed effects	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes

Notes: Only statistically significant outcomes are reported for each control state. All regressions include district FE, survey-year FE, subround FE, and demographic/housing controls. Standard errors clustered at the district level. $p < 0.10$, $p < 0.05$, $^{**}p < 0.01$.

Table 17: Tamil Nadu (Treated) vs Andhra Pradesh (Control)
Border-District Difference-in-Differences Estimates

	Casual Labour	Commuting Employment
Treated × Post	1.199*	0.403**
	(0.140)	(0.093)
Fixed effects	Yes	Yes
Controls	Yes	Yes

Notes: Only statistically significant outcomes are shown. All regressions include district FE, survey-year FE, subround FE, and demographic/housing controls. Standard errors clustered at the district level. $p < 0.10$, $p < 0.05$, $^{**}p < 0.01$.

Table 18: Delhi (Treated) vs Uttar Pradesh (Control)
Border-District Difference-in-Differences Estimates

	Casual Labour	Domestic Chores	Informal Self-Empl.	Total Travel
Treated × Post (Q1)	−1.142*	−0.235*	0.487*	−0.153*
	(0.000)	(0.052)	(0.171)	(0.064)
Treated × Post × Q2	−1.353*	—	—	—
	(0.000)			
Treated × Post × Q3	−0.236*	—	—	—
	(0.000)			
Treated × Post × Q4	−0.845*	—	—	—
	(0.000)			
Fixed effects	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes

Notes: Casual labour includes quartile heterogeneity (Q1 baseline). Other outcomes do not include quartile interactions. All models include district FE, survey-year FE, subround FE, and demographic/housing controls. Standard errors clustered at the district level. $p < 0.10$, $p < 0.05$, $^{**}p < 0.01$.

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