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Gendered Transport Subsidy and its Short Run Effect on Female Employment: Evidence from Delhi's Pink Pass Scheme

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Abstract

How does gender-specific transport subsidy for urban women affect their participation in the labour force? To answer this question, we study the Government of Delhi's pink pass scheme that made bus travel free for women since October 2019. Using the Time Use Survey of 2019 and employing two alternative difference-in-difference (DID) strategies and a triple difference (DDD) approach, we find weak evidence that the policy increased paid work and employment of women at the intensive margin by 30 to 50 minutes. Strikingly, we find that women from economically marginalized households experience large and statistically significant increases in paid work and employment *both* at the extensive and intensive margins. The pink pass scheme increases employment of women from economically marginalized group by 24 percentage points at the extensive margin and by 150 minutes at the intensive margin. Our study has important insights for policies addressing supply-side bottlenecks in improving female participation in paid work.

Keywords: Transport, Subsidy, Employment, Time Use, Gender

JEL Codes: J16, J18, J22, J28, R42

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1 Introduction

Indian cities need gender-responsive urban mobility and public spaces so that benefits of city-led economic growth can be more equitably distributed.

World Bank (2022): India - Toolkit for Enabling Gender Responsive Urban Mobility and Public Spaces.

Urban India has been characterized by a low and declining female workforce participation rate in the last decade. According to Deshpande and Singh (2021), during the period 2016-2019, the urban female labour force participation rate in India fell from 22% to 11%. This is accompanied by a steady but less sharp decline in the female employment rate from 11% to 7%.[1] Development researchers have often emphasized that the presence of safe and affordable transport has the ability to create conditions that encourage the participation of women in economic and social life in South Asia (Muralidharan and Prakash, 2017; Cheema et al., 2022; Field and Vyborny, 2022; World Bank, 2022; Shah et al., 2023). Summarizing research papers on this issue, World Bank (2022) states, 'Barriers to women's mobility actively restrict their choices around education and employment'. Studying the gender-specific commuting patterns based on a primary survey in Mumbai, Alam et al. (2021) show that 30 % of women outside the labour force find the absence of cheap, accessible and safe transport as a barrier to labour force participation. More importantly, Alam et al. (2021) find that women who cite long, expensive and unsafe transport systems as impediments are more likely (than other women) to accept work if available. Similar descriptive studies reveal that the gender blind design of urban public transport systems fails to accommodate the differential needs and alleviate the differential constraints faced by men and women in urban India (Anand and Tiwari, 2006; Shah et al., 2017; Mahambare and Dhanaraj, 2022).

In 2019, the government of National Capital Territory of Delhi (Government of Delhi) decided to completely subsidise fares for women travelling on intra-city buses. Women travelling in these buses were issued pink passes free of cost, and the government-owned bus corporations were later reimbursed an amount proportionate to the pink tickets issued. The objective of the government was to provide safe and affordable public transport for women who were underrepresented in the city's workforce as well as in public transport ridership. It was believed that such gender-specific

[1] Deshpande and Singh (2021) uses panel data from Consumer Pyramid Household Survey (CPHS) of the Centre for Monitoring Indian Economy (CMIE). This survey uses a more stringent definition of labour force participation and employment compared to the National Sample Survey or the Periodic Labour Force Survey. Hence the estimates are lower than those obtained from other datasets.

subsidies would weaken mobility constraints that women face and encourage labour participation (Kejriwal, 2019). Using a relevant sub-sample of the Time Use Survey 2019 (conducted by the Ministry of Statistics and Programme Implementation (MoSPI)) and two alternative designs of a difference in difference (DID) methodology and a Triple Difference (DDD) estimation strategy, we investigate if this policy intervention by the Government of Delhi led to an increase in female employment and female participation in paid work.

The rest of the paper is discussed as follows: Section 2 discusses the pink pass scheme passed by the Delhi government in 2019, section 3 describes the data, section 4 explains the empirical strategy, section 5 reports the results and section 6 concludes.

2 Description of the Pink Pass Scheme

In June 2019, the Aam Aadmi Party led Government of Delhi drafted a policy to make bus travel free for women which was finally implemented on October 29, 2019. Under this policy, women using a bus run by the state's bus corporations (Delhi Transport Corporation (DTC) and Delhi Integrated Multi-Modal Transport System (DMITS)) were not charged a fare and were issued a pink pass. The corporations got the fare reimbursed by the government at the rate of Rs. 10 per pink pass issued. The government estimated that this bus fare subsidy program would cost Rs. 3000 million to the state exchequer (Mathur, 2019).

The objective of the scheme was to provide safe and affordable transport for women who were underrepresented in the state's workforce and public transport ridership. The government expected the scheme to reduce the pecuniary and non-pecuniary cost of transport (for example, time cost) and hence improve access to education and employment for women (Kejriwal, 2019).

The scheme was extremely successful in increasing the representation of women in bus transport. According to government officials, approximately 1000 million pink tickets were issued in the period between October 2019 and January 2023 (Raj, 2023). This milestone was achieved in a city with 10 million women despite a strict lockdown implemented in the city during the period surrounding the first two waves of the COVID-19 pandemic. The representation of women in bus ridership also increased steadily by 10 % in the post-treatment period (Mahendru, 2022).

While, based on official data, the government claims the scheme to be a success, based on the increase in ridership, did the program achieve its target of improving workforce participation among women? By studying the impact of this gender-specific transport subsidy program on employment and paid work, we contribute to the literature that studies the impact of transport-induced spatial frictions that create an impediment to women's participation in socio-economic life.

3 Data

The data used in this study originates from the nationally representative Time Use Survey-2019 (TUS-2019), administered by the Ministry of Statistics and Programme Implementation (MoSPI) in 2019. TUS-2019 was designed to capture detailed information on time allocation, demographic attributes, and economic characteristics of a diverse sample of individuals. The survey collected data on individuals aged 6 years and above, focusing on their daily time use patterns. The reference period for this time-use information ranged from 4:00 AM on the day before the interview date to 4:00 AM on the interview day. This timeframe allowed for a comprehensive examination of how individuals allocate their time throughout the day.[2]

The TUS-2019 dataset comprises an extensive sample size, including data from 445,299 individuals drawn from 138,799 households in 9,946 distinct villages or urban wards, spanning 676 districts and representing 36 states or union territories within India. However, for the purposes of our study, we have limited our analysis to households and individuals exclusively sampled from *urban* areas within the state of Delhi and its neighbouring districts in Uttar Pradesh and Haryana.[3] For our analysis, we only consider individuals in the working age bracket (above 16 years and below 65 years).

[2]For each household, the survey collected information on time usage for every member aged 6 years and above. The reference period covered 24 hours, spanning from 4:00 AM on the day before the interview date to 4:00 AM on the interview day. For every 30-minute slot within this reference period, individuals were asked to report the activity they engaged in. Individuals had to choose an activity from an exhaustive list of 165 three-digit activities provided by the International Classification of Activities for Time Use Statistics 2016 (ICATUS-2016). These activities were grouped into 56 sets called Divisions, which were further grouped into 9 major divisions. In case more than one activity was performed during a 30-minute slot, individuals were asked to report one of the activities as the major activity and the rest as minor activities. If only the time used on major activities is considered, then for every individual the time spent on major activities adds up to 24 hours (1440 minutes). As the data does not specify the relative importance of major and minor activities, the analysis in this paper is solely based on the time spent on major activities.

[3]In addition to the nine districts of the state of Delhi, the districts being considered for some analyses in this paper are as follows: Gautam Budh Nagar, Ghaziabad, Faridabad, Gurgaon, Jhajjar and Sonipat.

In the TUS-2019 time survey, it is not the case that households located in certain regions are surveyed earlier or later during the survey period. Within every region, there are households are surveyed during a particular month of the year. Thus when a household is surveyed during the survey period is not related to household characteristics. Since the Pink Pass program was implemented on 29 October 2019, there exists households that were surveyed *before* the treatment and households that were surveyed *after* the treatment. To account for the implementation timing of the pink pass program, we introduce a binary variable denoted as $Post$. This variable takes on the value of 1 if the household or individual was surveyed after the scheme's implementation date, and 0 otherwise.

We use six variables as potential outcomes. First, we have two variables measuring paid work. We have an indicator variable that takes the value of 1 if an individual has spent any positive amount of time in paid work. Additionally, another variable measures the amount of time an individual spent in paid work in minutes. Secondly, we have two variables measuring employment participation: one at the extensive margin (an indicator variable denoting participation) and the other at the intensive margin (a continuous variable measuring employment in minutes).[4] In addition to these four variables, we use time spent on employment outside house and time spent traveling, both measured in minutes, as two additional outcome measures. In addition to the six outcome variables and the two variables defining the treatment period and treatment group, we use a host of individual and household level controls like age, years of schooling, schooling of household head, religion, caste, access to Liquefied Petroleum Gas (LPG) as primary cooking fuel and *pucca* house.[5]

[4]In TUS-2019, time spent on activities related to self-employment, wage & salary work, and casual labour for production of goods and services is defined as paid work. Time spent on employment and related activities (Major Division 1) refers to employment in government, corporations, non-profit institutions, household enterprises for the production of goods and services, employment related ancillary activities, training and studies related to employment, seeking employment, setting up business, employment related travel etc. The two categories have significant overlaps but are not identical. Since our employment indicator is based on an individual's time use on a single day and an individual is defined as employed if they have any positive time spent on employment activities, our estimates of employment differ significantly from estimates based on usual principal status from National Sample Surveys or Periodic Labour Force Survey.

[5]Table B1 in the online appendix describes the data by reporting the averages and dispersion of the variables used in our analysis.

4 Empirical Strategy

This paper relies on two alternative differences in differences (DID) strategies to identify the effect of the pink pass scheme on various work participation variables. In both cases, women in Delhi constitute the treatment group and the period after October 2019 is the post-treatment period.

In the first set-up, we consider Delhi men as the relevant control group. The estimating equation is as follows:

$$\begin{aligned} Y_{ihdt} &= \beta_0 + \beta_1 Post_t + \beta_2 Female_{ihd} + \beta_3(Post_t \times Female_{ihd}) \\ &\quad + X_{ihd}\alpha + Z_{hd}\gamma + \kappa_h + M_t + \delta_d + \varepsilon_{ihdt} \end{aligned} \tag{1}$$

where Y_{ihdt} is the outcome variable for the i^{th} individual in household h in district d which is surveyed in date t. $Female$ is a dummy variable indicating that an individual is female. $Post$ is an indicator variable that takes value one if the household is surveyed in the period after the scheme was launched. X is a vector of individual controls. Z is a vector of household controls. κ and $delta$ denote household and district fixed effects. M denotes month of survey fixed effects. It should be noted that in specifications where the household fixed effects κ are introduced, month fixed effects, district fixed effects, household controls and the variable $Post$ are dropped. A specification with household fixed effect is our preferred specification, as it absorbs all controls that vary at the household or district level, and only uses within household variation to identify the treatment effect. If the parallel trend assumption holds, the coefficient β_3 quantifies the treatment effect of the pink pass program. We test for parallel trend in the outcome variables for men and women in Delhi for the weeks/months of 2019 preceding the implementation of the program. We also conduct an event study estimation to confirm the absence of differential pre-trends and anticipation effects.[6]

In the second DID set up, we treat working age women in the urban areas of districts (of other states) surrounding Delhi as the relevant control group. The estimating equation is as follows:

$$Y_{ihdt} = \beta_0 + \beta_1 Post_t + \beta_3(Post_t \times Delhi_d) + X_{ihd}\alpha + Z_{hd}\gamma + M_t + \delta_d + \varepsilon_{ihdt} \tag{2}$$

[6] The sample size is not very large and households survey dates are spread over the entire year. An event study estimates a coefficient for each lag and lead term period. Therefore we use a wider definition of a two-months period is defined as an unit time. Thus the year is divided into six time periods. The fifth time period is the period preceding the treatment initiation and defined as period 0. Therefore, there are four pre-treatment periods and one post-treatment period, each of which has separate coefficients estimated.

where $Delhi$ is an indicator variable that takes value 1 if the individual is from Delhi. As before, if the parallel trend assumption is satisfied, the coefficient β_3 measures the treatment effect of the pink pass program. We test for parallel trend in the outcome variables for Delhi women and urban women of neighbouring districts for the weeks/months of 2019 preceding the implementation of the program.

Our empirical strategy also uses a difference in difference in difference or triple difference set up by combining the two alternative DID set ups. The first difference is over the survey period, the second difference is over gender and the third difference is over geographic boundaries.

$$\begin{aligned} Y_{ihdt} &= \beta_0 + \beta_2 Female_{ihd} + \beta_3(Post_t \times Female_{ihd} \times Delhi_d) \\ &\quad + \beta_4(Female_{ihd} \times Delhi_d) + \beta_5(Female_{ihd} \times Post_t) + X_{ihd}\alpha + \kappa_h + \varepsilon_{ihdt} \end{aligned} \tag{3}$$

The inclusion of household fixed effects implies that we do not have to include the variables $Post$, $Delhi$ and their interaction in the regression function. β_3 is the coefficient of interest. We test for parallel trend in triple difference for the period before the treatment.

In 2019, Delhi was and still remains one of the wealthiest regions in India.[7] Approximately 21% and 39% of households in urban Delhi have personalized four wheeler and two wheeler ownership respectively (Govt. of Delhi, 2020). In addition to the fact that a large proportion of households have access to private transport (excluding bicycles), the Delhi Metro has become a convenient and faster albeit costlier alternative to public buses as a mode of public transport (Suman et al., 2016).[8] In such a scenario, it is expected that bus transport is especially important for individuals from economically marginalized households that do not have access to private transport or more expensive modes of public transport. Based on a survey of 10 bus routes in Delhi, Suman et al. (2016) finds that approximately 75% of frequent bus users approximately have a household monthly income of less than Rs.30000. In the light of this, the pink pass program is expected to have a large impact on economically marginalized women. In order to test this hypothesis, we use the absence of LPG as primary cooking fuel' as an indicator of economic marginalization [9] and estimate the two DID models and the DDD model separately for individuals with and without LPG as primary

[7]Delhi has a per capita income three times higher than the national average. It held the second position among all states and union territories in India in terms of per capita income (Govt. of Delhi, 2020).

[8]According to Suman et al. (2016), '57% of metro users are cannibalised from buses'.

[9]Approximately six percent of urban households in Delhi and 15% of urban households in neighbouring districts do not report LPG as their primary cooking fuel.

cooking fuel. We then test the hypothesis that the treatment effect is greater for individuals without access to LPG.[10]

5 Results

We start by reporting the results of the first DID specification (Equation 2) where working-age men in urban Delhi are used as the control group. In Table 1, we test for the existence of differences between the conditional pre-trend of the control and treatment groups. We use two alternative specifications depending on whether months or weeks are used a measure of unit time. For neither of the two specifications and for none of the six outcome variables, the coefficient of interaction between the treatment group and continuous time turns out to be statistically significant (at conventional levels of significance) for the pre-treatment period. Table B2 reports the results of the unconditional (without controls other than continuous time, treatment indicator and their interaction) pre-trend test. None of the twelve interaction terms are statistically significant even at a 10% level of significance.

In Table 2 we report the results of the estimation of Equation 2. For the specification in this table, we do not include household fixed effects and thus also use the variation across households (within a district) for identification. The table notes of the table describe the individual and household level controls used. As is expected, the coefficient of $Female$ is large and significant, indicating the gender imbalance in labour force participation in the period prior to the treatment. The coefficient of the variable $Post$ is economically and statistically insignificant indicating no effect of the treatment on men in Delhi. For most variables, the treatment effect denoted by the coefficient of the interaction term ($Post \times Female$) is positive denoting that the pink pass scheme increases female labour participation. However, most of the effects are not statistically significant at even a 10% significance level. The effect on paid work (55 minutes) and employment (58 minutes) is significant at 10% significance level. In other words, the pink pass scheme increased the time spent by women on paid work (employment) by approximately an hour. The effect sizes are economically large representing approximately 0.35 times the standard deviation of both the variables within women in Delhi.

[10] We also use the education level of household head and monthly per capita consumption expenditure (MPCE) as indicators of economic well being and conduct heterogeneity analysis by dividing the sample on the basis of the variables. However we use the absence of LPG as the primary cooking fuel as an indicator of economic marginalization, because it is a binary variable that is more likely to be reported with accuracy.

In Table 3 we report the results of the estimation of Equation 2 after including household fixed effects. The inclusion of household fixed effects allows us to control for all household-level variables but does allow us to observe the effect of the scheme on the control group. The large and significant coefficient of $Female$ reflects the gender imbalance and is similar in magnitude to the corresponding coefficients in Table 2. As in Table 2, we do not find any effect on the paid work and employment participation. The size and the significance of the treatment effect on paid work and employment (at the intensive margin) are also not affected by the inclusion of household fixed effects. The scheme increases the time spent by women on paid work (employment) by approximately an hour.

In Figure 1 we also report the results of an event study analysis using two outcome variables (Paid Work and Employment) that showed statistically significant effects in Table 2 and table 3. We use the regression framework of equation 2 with household fixed effects. However, we allow for the estimation of treatment effects separately for a lag and multiple lead periods, using the period preceding the treatment as the omitted category. The control group continues to be men in urban areas of Delhi. For all lead periods, the treatment effect is statistically insignificant at a 10% level, thus reinforcing the claim of parallel pre-trends for the treatment and control group. It also provides suggestive evidence for the absence of anticipation effects. For the lag period (Nov-Dec), we find statistically significant effects similar in magnitude to the effect reported in Table 2 and Table 3.[11]

We now report the results of the second DID specification (Equation 2) where women from urban areas of Delhi's neighbouring areas are used as the control group. We first report the results of the test for differential conditional pre-trend in Table 4. The table reports the coefficient for the interaction term ($Delhi \times t$), where t is either measured using weeks or months. None of the twelve coefficients reported are significant even at a 10% significance level. Table B3 in the online appendix reports the results of the test for unconditional pre-trends and we do not find evidence against parallel pre-trends.

In Table 5, we report the estimation results of equation 2. The coefficient of $Post$ is insignificant indicating that the scheme had no effect on urban women from neighbouring districts of Delhi. The variable of interest is ($Post \times Delhi$) which is significant at 10% level when the outcome variable

[11] As a falsification test, we also conduct an event study estimation for the non-working age population (individuals outside (16-65) age bracket). The results are reported in Figure B1 of the online appendix. None of the lag coefficients are statistically significant indicating no impact of the scheme on men's employment and paid work.

is paid work measured in minutes. However, there is no effect on either paid work or employment at an extensive margin. While the effect of employment measured in minutes is insignificant, the scheme increases outside-home employment by 39 minutes. This effect is significant at a 5% significance level. Since the standard errors are clustered at a district level and the number of districts is much lower than 42, we report the Wild Bootstrapped p-values for the significance test of the interaction terms. Bootstrapping leads to a loss of significance for paid work. However, the effect on outside home employment continues to be significant at 5% significance level.[12]

We also conduct a triple difference estimation of the treatment effects by estimating Equation 4 after checking for the appropriate version of the parallel trend assumption (Table B7). We find no evidence of a violation of the appropriate parallel trend assumption. The results are reported in the first row of Table 8. While the treatment effect is positive and similar in magnitude to the DID estimates of Table 5, the coefficients are not significant even at a 10% level of significance.

The above results point to the fact that there is weak evidence that the pink pass scheme led to a moderate increase in the average work participation of Delhi women. However, it is more important to study the effect of this scheme on women who are potential users of public bus transport and are unlikely to have access to private substitutes or expensive substitutes of bus transport.

Heterogeneity Results:

As mentioned earlier in section 4 a large proportion of Delhi's households have access to private transport and public transport, especially public bus transport is largely used by households with limited means. We use the absence of access to clean cooking fuel (LPG) as an indicator of economic marginalization. In India, most urban households use LPG as a cooking fuel. Economically marginalized households use kerosene and biomass fuel as primary cooking fuels (Kis, 2017; of India, 2019; Sati et al., 2022; Sreenivasan et al., 2023). We divide the population into individuals from households with LPG access and those without. We then estimate the treatment effect for these two subpopulations using the three identification strategies discussed earlier.[13]

[12]In Table B4 we conduct a falsification test by estimating equation 2 for the sample of working-age men from Delhi and neighbouring districts. Men from Delhi are the pseudo-treatment group while men from neighbouring districts constitute the control group. The treatment effect is small in magnitude and statistically insignificant indicating no impact of the scheme on men's labour participation outcomes.

[13]We also use MPCE cut-offs as indicators of economic marginalization. Unlike consumption data of National Sample Surveys which is based on a definite recall period and a detailed questionnaire, TUS-2019 asks households to

In Table 6 we report the heterogeneity results estimated using the first DID set-up where working-age men in Delhi are used as controls. For individuals from households without LPG access, the pink ticket scheme increases paid work and employment participation both at an extensive margin and an intensive margin. At an extensive margin, paid work and employment participation rate increases by 39% and 24% respectively. While these effects are indeed large and significant, it should be kept in mind that we adopt a liberal definition where someone is said to be engaged in paid work or employment on a day if she/he is engaged in such activity for any positive amount of time. The pink ticket scheme increases paid work by 130 minutes, employment by 150 minutes and outside-home employment by 141 minutes for the economically marginalized sub-population. For individuals with LPG access, there exists much smaller treatment effects for paid work and employment at an intensive margin but the coefficients are significant at a 10% significance level. For none of the other variables, the effect is significant. We test for the difference in effect for the two subpopulations and reject the hypothesis the effect size for both the groups are equal.[14]

In Table 6 we report the heterogeneity results estimated using the second DID set-up where working-age urban women in Delhi's neighbouring districts are used as controls. For individuals from households without LPG access, the pink ticket scheme increases paid work and employment participation both at an extensive margin and an intensive margin. Paid work and employment participation increased by 28% and 26% respectively. The time spent in either of these two activities increases by 147 minutes and 195 minutes respectively. No such effect is found for the population with LPG access. In Table 8, we also report the heterogeneity results for the triple difference set-up. We find similar strong results from individuals without LPG access and an absence of any impact on individuals with LPG access.

The last two rows of Table 8, report the heterogeneity results in a triple difference framework. We again find that the treatment effects are large, positive and statistically significant for the marginalized group and not so for the non-marginalized group.

report MPCE of a usual month. *LPG access* is a binary variable that is expected to be reported with more accuracy than *MPCE on a usual month* that is based on a guesstimate that is more subject to errors. Such measurement errors can be expected to be correlated to observed MPCE, thus leading to attenuation bias.

[14]Results of a heterogeneity analysis where the population is divided on the basis of MPCE is reported in Table B5. A household with MPCE below Rs. 2000 is defined as a *low-MPCE household* For female individuals from low MPCE households, there is a large positive effect on paid work, employment and employment outside house in the intensive margin. However, no such effect is there at the intensive margin.

6 Conclusion

The pink ticket scheme introduced by the Delhi government in 2019 was to the best of our knowledge the first gender specific transport subsidy scheme in India. Since the challenges faced by women in accessing public transport is unique, it was believed that such a scheme will be able to address those problems. One of the stated objectives of the government was to promote work force participation by women. Since 2019, a number of Indian states have adopted the a policy of gender specific public transport subsidy with the stated aim of encouraging work participation among women (Tamil Nadu Zero Ticket Bus Travel Scheme for Women (2021), Nari ko Naman Scheme in Himachal Pradesh (2022), Shakti Scheme in Karnataka (2023)). While the Delhi government claimed success for their scheme, based on the uptake of this scheme, this paper evaluates if the scheme in Delhi led to an increase in work participation among women in the period right after its launch.[15]

We find that there is a weak evidence that the scheme lead to an improvement in female work force participation at an aggregate level. However, more importantly, for the economically marginalized sections of the society, we find large and statistically significant effects on work participation. This suggests that the scheme was successful at least in achieving its objective for a section of the population that is most likely to be affected by the availability of affordable public transport.

Our results have important policy implications for the design of urban public transport and policies to encourage female employment. The positive effect on female employment does suggest to the presence of bottlenecks that impede participation in the labour market. This in turn suggests the low urban female work participation is not only a supply side phenomenon. While gendered social norms are indeed a reality in South Asia, they can be weakened through intelligent design of incentives. Secondly, the presence of large effects for marginalized populations also suggests that universal programs[16] can sometimes lead to self-selection of intended beneficiaries. Incorporating targeting based on unobserved characteristics into the design of the scheme is an inefficient alternative as it involves costs (example, verification cost, documentation cost) for both beneficiaries and the implementation agency.

[15] The nature of the TUS-2019 data does not allow us to study the long run consequences of the scheme

[16] The pink pass scheme was targeted towards women but universal within the population of women.

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APPENDICES

A Tables and Figures

Table 1: Checking for Conditional Pre-Trends: Coefficient for ($Female \times t$)

(Control Group: Male Individuals in Urban Delhi)

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable					
	Paid Work		Employment		Outside Home	
	Indicator	Mins	Indicator	Mins	Employment	Travel
Female × Week Number	-0.00	-0.94	-0.00	-0.43	-0.88	0.19
	(0.00)	(1.01)	(0.00)	(0.94)	(0.95)	(0.24)
Observations	4052					
Female × Month Number	-0.00	-4.05	-0.01	-1.88	-3.72	0.75
	(0.01)	(4.27)	(0.01)	(4.03)	(4.03)	(1.00)
Observations	4102					

Notes

a) These are estimates of the coefficient of the interaction between the indicator variable $Female$ and the continuous time variable t. Urban Delhi women as the treatment group and urban Delhi men as the control group.

b) All dependent variables are measured in minutes unless mentioned otherwise.

c) Standard Errors, clustered at the urban ward level reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

e) Controls used for each of the columns are as follows: Schooling (in years), age (in years), Household Size, Schooling of Household Head (in years), Pucca House (Indicator), LPG access (Indicator), official caste categories, religion, the month of survey and district fixed effects.

Table 2: Effect of 'Pink Tickets' on Female ($16 < age < 65$) Employment: DID Estimates

(Control Group: Urban Male Individuals in Delhi)

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable					
	Paid Work		Employment		Outside Home	
	(Indicator)	(Mins)	(Indicator)	(Mins)	Employment	Travel
Post	-0.07	-47.03	-0.00	-44.10	-13.16	5.26
	(0.05)	(28.62)	(0.03)	(28.11)	(29.77)	(6.29)
Female	-0.58***	-331.44***	-0.59***	-359.18***	-328.71***	-37.65***
	(0.02)	(11.27)	(0.02)	(10.84)	(11.42)	(2.97)
Post × Female	0.09	56.44*	0.02	59.38*	36.08	-6.81
	(0.06)	(33.47)	(0.05)	(32.40)	(32.46)	(6.03)
Observations	4816					

Notes

a) These are DID estimates with urban Delhi women as the treatment group and urban Delhi men as the control group.

b) All dependent variables are measured in minutes unless mentioned otherwise.

c) Standard Errors, clustered at the urban ward level reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

e) Controls used for each of the columns are as follows: Schooling (in years), age (in years), Household Size, Schooling of Household Head (in years), Pucca House (Indicator), LPG access (Indicator), official caste categories, religion, the month of survey and district fixed effects.

Table 3: Effect of 'Pink Tickets' on Female ($16 < age < 65$) Employment: DID Estimates with HH Fixed Effects

(Control Group: Urban Male Individuals in Delhi)

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable					
	Paid Work		Employment		Outside Home	
	(Indicator)	(Mins)	(Indicator)	(Mins)	Employment	Travel
Female	-0.60***	-341.20***	-0.61***	-369.25***	-341.33***	-40.35***
	(0.02)	(11.35)	(0.02)	(10.95)	(11.72)	(2.76)
Post × Female	0.08	55.20*	0.01	57.68*	35.38	-8.90
	(0.06)	(32.17)	(0.04)	(30.83)	(31.11)	(6.49)
Observations	4558					

NOTES

a) These are DID estimates with urban Delhi women as the treatment group and urban Delhi men as the control group.

b) All dependent variables are measured in minutes unless mentioned otherwise.

c) Standard Errors, clustered at the urban ward level reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

e) Controls used for each of the columns are as follows: Schooling (in years), age (in years) and household fixed effects.

Table 4: Checking for Conditional Pre-Trends: Coefficient for ($Delhi \times t$)

(Control Group: Female Individuals in Urban area's of Delhi's neighbouring districts)

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable					
	Paid Work		Employment		Outside Home	
	(Indicator)	(Mins)	(Indicator)	(Mins)	Employment	Travel
Delhi × Week Number	0.00	0.22	-0.00	-0.12	-0.09	-0.12
	(0.00)	(0.52)	(0.00)	(0.58)	(0.57)	(0.19)
Observations	2905					
Delhi × Month Number	-0.00	0.71	-0.01	-1.03	-0.60	-0.15
	(0.01)	(1.98)	(0.01)	(2.09)	(2.09)	(0.92)
Observations	2939					

Notes

a) These are estimates of the coefficient of the interaction between the indicator variable *Delhi* and the continuous time variable t. Urban Delhi women as the treatment group and urban women from neighbouring districts as the control group.

b) All dependent variables are measured in minutes unless mentioned otherwise.

c) Standard Errors, clustered at the district level reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

d) Since number of districts are less than 42, we also test the significance of the interaction term after Wild Bootstrapping standard errors. As is expected, bootstrapping increases p-values for the interaction term, and the coefficients continue to be insignificant at 10% significance level.

e) Controls used for each of the columns are as follows: Schooling (in years), age (in years), Household Size, Schooling of Household Head (in years), Pucca House (Indicator), LPG access (Indicator), official caste categories, religion, the month of survey and district fixed effects.

Table 5: Effect of 'Pink Tickets' on Female ($16 < age < 65$) Employment: DID Estimates

(Control Group: Female Individuals in Urban area's of Delhi's neighbouring districts)

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable					
	Paid Work		Employment		Outside Home	
	(Indicator)	(Mins)	(Indicator)	(Mins)	Employment	Travel
Post	0.10	66.49	0.10	63.07	44.87	9.79
	(0.14)	(68.15)	(0.14)	(66.15)	(66.43)	(7.41)
Post × Delhi	0.05	29.51*	0.03	32.80	38.99**	-1.34
	(0.04)	(16.16)	(0.04)	(18.93)	(17.44)	(5.98)
Bootstrapped p-value	[0.23]	[0.10]	[0.45]	[0.12]	[0.05]	[0.87]

NOTES

a) These are DID estimates with urban Delhi women as the treatment group and neighbouring district urban women as the control group.

b) All dependent variables are measured in minutes unless mentioned otherwise.

c) The number of observations for each column is 3493. Standard Errors, clustered at the district level reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

d) Wild Bootstrapped p-values for the interaction term (used since the number of districts is less than 42), reported in square brackets.

e) Controls used for each of the columns are as follows: Schooling (in years), age (in years), Household Size, Schooling of Household Head (in years), Pucca House (Indicator), LPG access (Indicator), official caste categories, religion, the month of survey and district fixed effects.

Table 6: Heterogeneity Analysis: Effect for HH with LPG access and those without access

(Control Group: Male Individuals in Urban area's of Delhi)

		(1)	(2)	(3)	(4)	(5)	(6)
Sub-Population	N	Dependent Variable					
		Paid Work		Employment		Outside Home	
		(Indicator)	(Mins)	(Indicator)	(Mins)	Employment	Travel
LPG : No	260	0.39***	130.56***	0.24**	150.34***	141.41***	22.97
		(0.11)	(40.20)	(0.10)	(43.71)	(44.79)	(15.72)
LPG : Yes	4298	0.07	53.32*	0.00	54.66*	31.37	-10.54
		(0.05)	(30.93)	(0.04)	(29.22)	(29.75)	(6.53)
($\triangle$ DID estimate= 0) pvalue		0.004	0.11	0.02	0.06	0.04	0.05

NOTES

a) First row estimates the treatment effect on women from households without LPG access. Second row is the effect for women from households with LPG access. The last row tests if the difference between the two rows are significant. For both sub-population of households, men from the same households act as controls.

b) All dependent variables are measured in minutes unless mentioned otherwise.

c) Standard Errors, clustered at the urban ward level level reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

e) Controls used for each of the columns are as follows: Schooling (in years), age (in years) and household fixed effects fixed effects.

Table 7: Heterogeneity Analysis: Effect for HH with LPG access and those without access

(Control Group: Female Individuals in Urban area's of Delhi's neighbouring districts)

		(1)	(2)	(3)	(4)	(5)	(6)
Sub-Population	N	Dependent Variable					
		Paid Work		Employment		Outside Home	
		(Indicator)	(Mins)	(Indicator)	(Mins)	Employment	Travel
LPG: No	272	0.28***	147.28***	0.26***	195.89***	203.98***	71.93***
		(0.06)	(26.24)	(0.07)	(34.05)	(39.76)	(13.39)
LPG: Yes	3218	-0.01	8.01	-0.03	6.67	14.52	-4.90
		(0.05)	(23.75)	(0.04)	(25.56)	(23.03)	(5.27)
($\triangle$ DID estimate= 0) pvalue (Wild Bootstrapped)		0.05	0.02	0.07	0.02	0.06	0.08

NOTES

a) The First row estimates the treatment effect on women from households without LPG access. The second row is the effect of women from households with LPG access. The last row tests if the difference between the two rows is significant. Wild Bootstrapped p-values of the test are reported. For both sub-populations of households, women from Delhi's neighbouring districts act as controls.

b) All dependent variables are measured in minutes unless mentioned otherwise.

c) Standard Errors, clustered at the district level reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

e) Controls used for each of the columns are as follows: Schooling (in years), age (in years), pucca house residence, religion, caste and district fixed effects.

Table 8: Triple Difference Results: Coefficient of $Delhi \times Female \times PostPeriod$

		(1)	(2)	(3)	(4)	(5)	(6)
Sub-Population	N	Dependent Variable					
		Paid Work		Employment		Outside Home	
		(Indicator)	(Mins)	(Indicator)	(Mins)	Employment	Travel
All Households	7129	0.07	35.36	-0.02	38.67	22.09	-11.67
		(0.08)	(46.27)	(0.07)	(46.63)	(47.95)	(8.95)
LPG: No	535	0.44***	144.54**	0.25	180.87**	174.81**	35.87*
		(0.15)	(70.83)	(0.15)	(72.30)	(72.20)	(18.64)
LPG: Yes	6594	0.06	36.24	-0.01	36.43	18.86	-15.11
		(0.08)	(48.55)	(0.07)	(50.21)	(51.92)	(10.03)

NOTES

a) The first row estimates the treatment effect for all treated women. The second row estimates the treatment effect on treated women from households without LPG access. The third row is the effect for treated women from households with LPG access.

b) All dependent variables are measured in minutes unless mentioned otherwise.

c) Standard Errors, clustered at the urban ward level level reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

e) Controls used for each of the columns are as follows: schooling (in years), age (in years) and household fixed effects.

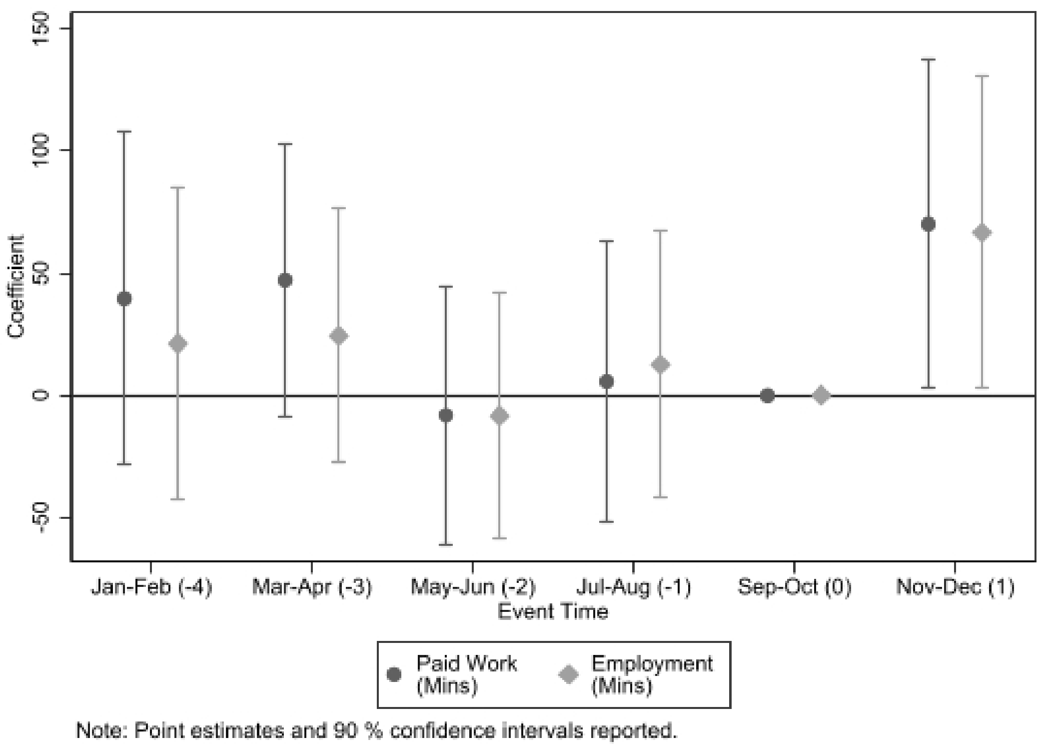

Figure 1: Event Study Coefficients: Trends in Employment and Paid Work

B Online Appendix

Table B1: Summary of the Sample Data

Individual Level Variables				
	Delhi		Neighbour Districts	
	Men (N=2,633)	Women (N=2,274)	Men (N=1,514)	Women (N=1,264)
Paid Work				
Indicator	0.71 (0.45)	0.14 (0.35)	0.73 (0.44)	0.15 (0.35)
Minutes	383.46 (272.44)	58.51 (160.96)	371.45 (245.38)	59.93 (155.19)
Employment				
Indicator	0.76 (0.43)	0.16 (0.36)	0.74 (0.44)	0.16 (0.37)
Minutes)	419.56 (279.35)	66.34 (176.39)	402.88 (261.57)	68.12 (171.35)
Outside Home				
Employment Minutes	388.86 (287.41)	61.84 (171.29)	390.48 (267.97)	63.96 (167.61)
Travel Minutes	61.04 (78.32)	20.71 (64.80)	68.52 (56.91)	20.32 (46.65)
Age (Years)	34.86 (12.29)	35.96 (12.52)	34.26 (11.99)	35.47 (12.46)
Schooling (Years)	10.94 (4.36)	9.82 (5.39)	11.00 (4.87)	9.86 (5.80)

Table B1: Summary of the Sample Data

Household Level Variables		
	Delhi	Neighbour Districts
	(N=642)	(N=438)
Post	168 (26.8%)	120 (27.5%)
Household Size	4.00 (1.97)	3.99 (2.20)
Schooling-HH Head (Years)	8.80 (5.29)	8.74 (5.65)
Religion		
Hinduism	406 (63.2%)	336 (76.7%)
Islam	146 (22.7%)	76 (17.4%)
Caste		
Scheduled Tribe	64 (10.0%)	16 (3.7%)
Scheduled Caste	151 (23.5%)	117 (26.7%)
Other Backward Class	161 (25.1%)	148 (33.8%)
LPG Access	581 (90.5%)	332 (75.8%)
Pucca House	570 (88.8%)	379 (86.5%)

NOTES:
For ratio or interval variables, mean is reported and standard deviation reported in parenthesis.
For indicator variables, the number and proportion of observations with variable value 1 is reported.
The objective of this table is to describe the data and not report estimates of population parameters. Hence sampling weights have not been used.

Table B2: Checking for Unconditional Pre-Trends: Coefficient for ($Female \times t$)

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable					
	Paid Work		Employment		Outside Home	
	(Indicator)	(Mins)	(Indicator)	(Mins)	Employment	Travel
Female × Week Number	-0.00	-0.92	-0.00	-0.42	-0.91	0.19
	(0.00)	(1.03)	(0.00)	(0.96)	(0.96)	(0.25)
Observations	4052					
Female × Month Number	-0.00	-3.81	-0.01	-1.71	-3.68	0.79
	(0.01)	(4.36)	(0.01)	(4.12)	(4.11)	(1.02)
Observations	4102					

Notes

a) These are estimates of the coefficient of the interaction between the indicator variable $Female$ and the continuous time variable t. Urban Delhi women as the treatment group and urban Delhi men as the control group.

b) All dependent variables are measured in minutes unless mentioned otherwise.

c) Standard Errors, clustered at the urban ward level reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

e) No additional controls are used in these regressions.

Table B3: Checking for Unconditional Pre-Trends: Coefficient for ($Delhi \times t$)

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable					
	Paid Work		Employment		Outside Home	
	(Indicator)	(Mins)	(Indicator)	(Mins)	Employment	Travel
Delhi × Week Number	-0.00	0.11	-0.00	-0.29	-0.26	-0.18
	(0.00)	(0.56)	(0.00)	(0.59)	(0.60)	(0.22)
Observations	2905					
Delhi × Month Number	-0.00	0.55	-0.01	-1.13	-0.88	-0.67
	(0.01)	(2.46)	(0.01)	(2.63)	(2.62)	(0.94)
Observations	2939					

NOTES

a) These are estimates of the coefficient of the interaction between the indicator variable *Delhi* and the continuous time variable t. Urban Delhi women as the treatment group and urban women from neighbouring districts as the control group.

b) All dependent variables are measured in minutes unless mentioned otherwise.

c) Standard Errors, clustered at the district level reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

d) Wild Bootstrapped p-values for the interaction term (used since the number of districts is less than 42), reported in square brackets.

e) No additional controls are used in these regressions.

Table B4: Effect of 'Pink Tickets' on Male ($16 < age < 65$) Employment and Travel

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable					
	Paid Work		Employment		Outside Home	
	(Indicator)	(Mins)	(Indicator)	(Mins)	Employment	Travel
Post	-0.06	-11.49	-0.20	-33.08	-46.40	-13.63
	(0.19)	(95.70)	(0.15)	(94.26)	(95.20)	(8.48)
Post × Delhi	-0.01	5.75	0.06	7.71	31.88	11.20
	(0.08)	(36.68)	(0.05)	(38.85)	(47.79)	(10.62)
Bootstrapped p-value	[0.86]	[0.88]	[0.32]	[0.83]	[0.56]	[0.38]

NOTES

a) These are DID estimates with urban Delhi women as the treatment group and neighbouring district urban women as the control group.

b) All dependent variables are measured in minutes unless mentioned otherwise.

c) The number of observations for each column is 4091. Standard Errors, clustered at the district level reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

d) Wild Bootstrapped p-values for the interaction term (used since the number of districts is less than 42), reported in square brackets.

e) Controls used for each of the columns are as follows: Schooling (in years), age (in years), Household Size, Schooling of Household Head (in years), Pucca House (Indicator), LPG access (Indicator), official caste categories, religion, the month of survey and district fixed effects.

Table B5: Heterogeneity Analysis: Effect for HHs with low MPCE and Others

(Control Group: Male Individuals in Urban area's of Delhi)

		(1)	(2)	(3)	(4)	(5)	(6)
Sub-Population	N	Dependent Variable					
		Paid Work		Employment		Outside Home	
		(Indicator)	(Mins)	(Indicator)	(Mins)	Employment	Travel
Low MPCE	235	0.15	119.51**	0.12	124.73**	104.52*	4.61
		(0.13)	(48.33)	(0.10)	(48.25)	(53.29)	(11.12)
Others	4323	0.08	50.36	0.00	52.64	30.39	-9.83
		(0.06)	(33.91)	(0.05)	(32.62)	(32.78)	(7.09)
($\triangle$ DID estimate= 0) pvalue		0.56	0.20	0.28	0.18	0.20	0.28

NOTES

a) First row estimates the treatment effect on women from households without low MPCE. Second row is the effect for women from households without low MPCE. The last row tests if the difference between the two rows are significant. For both sub-population of households, men from the same households act as controls.

b) All dependent variables are measured in minutes unless mentioned otherwise.

c) Standard Errors, clustered at the urban ward level level reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

e) Controls used for each of the columns are as follows: Schooling (in years), age (in years) and household fixed effects fixed effects.

Table B6: Falsification Test for Heterogeneity Result: Effect for HH with LPG access and those without access

(Control Group: Male Individuals in Urban area's of Delhi's neighbouring districts)

		(1)	(2)	(3)	(4)	(5)	(6)
Sub-Population	N	Dependent Variable					
		Paid Work		Employment		Outside Home	
		(Indicator)	(Mins)	(Indicator)	(Mins)	Employment	Travel
LPG: No	342	-0.05	-49.31	0.07	-26.70	-22.38	54.05**
		(0.08)	(31.73)	(0.08)	(33.42)	(32.69)	(20.02)
LPG: Yes	3748	-0.03	9.48	0.03	6.28	34.62	8.29
		(0.09)	(47.82)	(0.05)	(51.59)	(60.45)	(11.52)
($\triangle$ DID estimate= 0) pvalue (Wild Bootstrapped)		0.78	0.20	0.55	0.50	0.37	0.53

NOTES

a) The first row estimates the treatment effect on men from households without LPG access. The second row is the effect of men from households with LPG access. The last row tests if the difference between the two rows is significant. Wild Bootstrapped p-values of the test are reported. For both sub-populations of households, men from Delhi's neighbouring districts act as controls.

b) All dependent variables are measured in minutes unless mentioned otherwise.

c) Standard Errors, clustered at the district level reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

e) Controls used for each of the columns are as follows: Schooling (in years), age (in years), pucca house residence, religion, caste and district fixed effects.

Table B7: Checking for Pre-Trends in DDD Model: Coefficient for ($Delhi \times Female \times t$)

	(1)	(2)	(3)	(4)	(5)	(6)
	Dependent Variable					
	Paid Work		Employment		Outside Home	
	(Indicator)	(Mins)	(Indicator)	(Mins)	Employment	Travel
Conditional Pre-Trends						
Delhi × Female × Week Number	0.00	-0.47	0.00	0.83	1.00	0.47
	(0.00)	(1.61)	(0.00)	(1.55)	(1.58)	(0.30)
Observations	5918					
Delhi × Female × Month Number	0.01	-3.65	0.00	1.55	2.25	1.70
	(0.01)	(6.91)	(0.01)	(6.66)	(6.83)	(1.28)
Observations	5978					
Unconditional Pre-Trends						
Delhi × Female × Week Number	0.00	-0.02	0.00	0.87	0.64	0.02
	(0.00)	(1.66)	(0.00)	(1.59)	(1.61)	(0.31)
Observations	6279					
Delhi × Female × Month Number	0.01	-0.67	0.00	2.95	2.25	0.04
	(0.01)	(7.11)	(0.01)	(6.83)	(6.92)	(1.31)
Observations	6346					

NOTES

a) These are estimates of the coefficient of the interaction between the indicator variables $Delhi$, the indicator variable $Female$ and the continuous time variable t.

b) All dependent variables are measured in minutes unless mentioned otherwise.

c) Standard Errors, clustered at the urban ward level reported in parenthesis. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

e) For the unconditional trend estimates, additional controls used for each of the columns are as follows: Schooling (in years), age (in years) and household fixed effects.

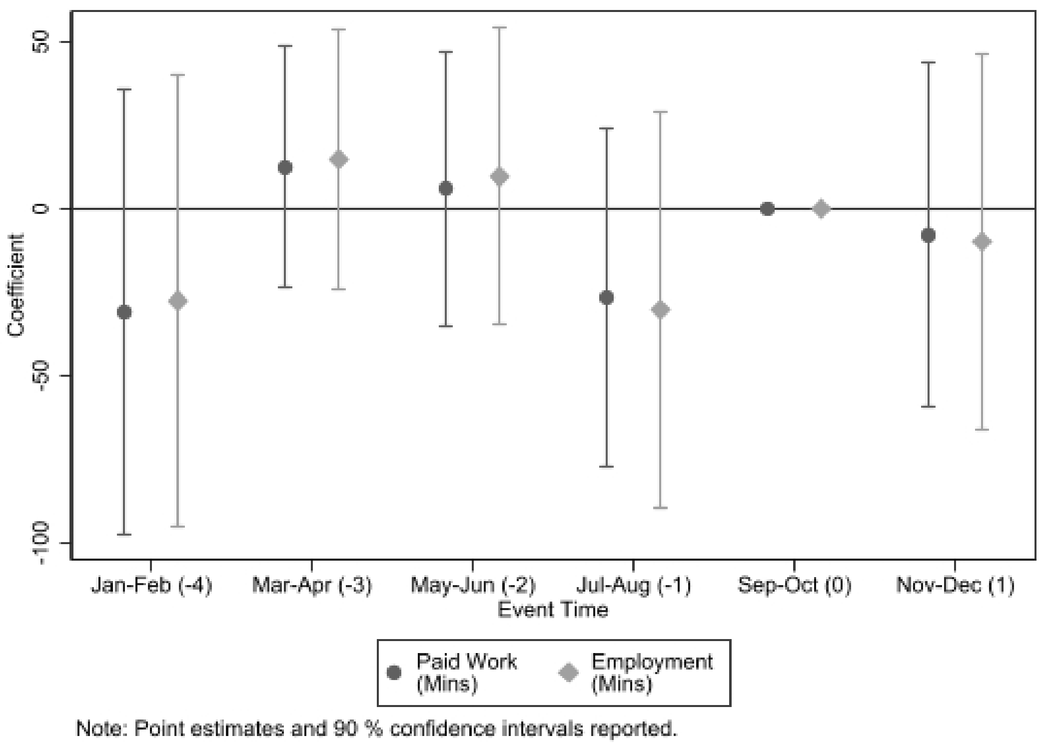

Figure B1: Event Study Coefficients: Trends in Employment and Paid Work for non-working age