Do Women-Only Train Cars Drive Female Labor Force Participation? Evidence from India

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I. Introduction:

Participation of women in the labor force varies widely across the world, primarily due to variation in economic, social, and cultural factors. In India, female labor force participation is among the lowest for emerging economies ("Labor Force Participation Rate", 2022). Data from the World Bank shows that female labor force participation in India has been declining since 2005. Researchers have explored this falling trend by looking at increasing female educational enrollment, availability of employment opportunities, rising household income, and measurement of informal work activities (Verick, 2014). While these studies help explain gender disparities in labor supply using sociocultural and economic determinants, a growing body of literature explores how physical structures constrain women's labor market activity. India's expanding economy has led to rising demand for transportation that is constrained by its limited supply of road infrastructure.

Our study uses the introduction of women-only train cars to extract previously unmeasurable causal relationships between perceived risk on public transportation and employment choices. While public transportation infrastructure expansion may boost female labor force participation, there continue to be pressing female safety concerns in India's public spaces. In 2009, India introduced eight "Ladies Specials" women-only trains in Delhi, Mumbai, Calcutta, and Madras to provide safe transportation for the growing population of working women. With this information, we can answer questions about how access to gender-specific transportation influences women's choices in urban areas. *First, do women-only train cars drive female labor force participation in Indian cities?* Recent survey data from the Observer Research Foundation (ORF) across 140 Indian cities found that women felt unsafe while traveling, with 52% of women surveyed reporting that these feelings have caused them to turn down education or work opportunities (Ratho and Jain, 2021). Thus, we expect that women-only train cars may decrease the safety risks of riding public transportation, leading to increases in female labor force participation. *Second, do the characteristics of these women matter?* Employment opportunities, especially highly-skilled and high-paying jobs, are often concentrated in city centers. We expect that women with higher education levels may be more willing to take on higher levels of risk due to higher costs of foregoing work opportunities in city centers.

To identify how perceived risk of harassment affects employment outcomes, we adopt a quasi-experimental approach which exploits household survey data around the establishment of women-only trains in Mumbai. We will use a retrospective survey to collect data on women's labor force participation from before and after the introduction of the train cars in villages near Ladies Specials or non-Ladies Special train lines. This makes it possible to use a differences-in-differences strategy to identify the causal effect of the establishment of women-only trains on outcomes for women living near these train lines in Mumbai.

The ORF survey also found that 56% of women reported that they have been sexually harassed while using public transport (Ratho and Jain, 2021). These statistics imply that public transportation is not only relevant to whether women choose to search for labor opportunities but that women are physically unsafe traveling on current modes of public transit. Therefore, it is of considerable economic and policy interest to identify effective and scalable strategies for increasing safe and convenient public transportation options for women in India and other similar developing countries.

The remainder of this paper is organized as follows. First, we discuss existing research related to female labor force participation, transportation infrastructure, decision-making in response to safety concerns, and the link between infrastructure and employment status. Second, we describe the Ladies Special program and background on the areas surveyed. Third, we present our empirical strategy and the data we plan to use to estimate our models. Finally, we offer concluding remarks and a quasi budget.

II. Literature Review:

In order to understand the relationship between women's labor force participation rates (LFPR) and gender-specific transportation infrastructure, we analyzed previous research on background and related topics. Mehrotra and Paida (2017) describe a recent fall in female LFPR in India due to widening educational opportunities for women and the increased mechanization of the agricultural sector. Results from this study anticipate that female LFPR across India will rise as women choose to enter the labor market following secondary and higher secondary education. A study by Chakraborty and Lohawala (2021) finds another factor in low female LFPR—the rate of crimes against women. Using a fixed-effects strategy and panel data from 2004-2012, Chakraborty and Lohawala find that an increase of one standard deviation in the incidence of sexual crimes per 1,000 women reduces the probability of a woman's employment outside the home by 9.4%. This study was helpful in confirming the connection between perceived safety and employment, and confirmed the need to investigate the impact of changes to travel on female employment rates in India.

Research also suggests that female decision-making regarding *travel* to schooling and employment is linked to perceived safety risk. Borker (2021) investigates why women in New Delhi choose inferior educational institutions at higher rates than men. By analyzing travel patterns and rates of crime in routes to different New Delhi colleges, Borker discovers that women more often choose a college in the bottom half of quality distributions over colleges in the top quintile in order to feel safe while traveling. This paper does not look at the changes in travel behavior in response to more infrastructure, nor does it evaluate the choices of women who have not entered secondary education or the labor market. It is helpful for evaluating the priorities of women in making decisions related to education and employment, but it likely underrepresents the role of safety by not surveying the considerable number of women who choose not to pursue further training in the face of safety risk.

Most studies regarding the connection between public transit and employment have been conducted in developed countries with substantially different labor markets, cultural contexts, and infrastructure than our chosen setting. A two stage least squares analysis of employment trends following infrastructure installation in Portland and Atlanta found a relationship between increased access to public transportation and labor force participation (Sanchez, 1999). In Sanchez' study we found many possible omitted variables, since distance from rail lines is likely correlated with employment through other mechanisms than infrastructure accessibility. The study also did not consider gender-based differences, but it still provided a helpful link in assessing the relationship between transit and employment. Additionally, the data collection method Sanchez employed inspired the survey system we plan to use. This involves sampling within a radius of 2.5 kilometers—the distance at which commuters would consider a train stop to be accessible.

A closer connection to our question about changes in female employment in response to infrastructure installation in developing countries came through a study examining the impact of BRT and light rail investments in Lima, Peru (Martinez, Mitnik, Salgado, et. al; 2018). It was helpful in establishing that transport infrastructure development in metropolitan areas led to gender-specific heterogeneous increases in employment and earnings per hour that benefited women. While the study reaches the conclusion that increased LFPR was connected to safety concerns in women, the strength of that causal relationship is weak, since the paper never details any perceived or actual differences in safety due to increases in public transit. The new transit systems are also not gender-specific, so any conclusions about increases in employment rates among women due to safety concerns likely underestimate the impact of more targeted transportation policies such as the Ladies Special.

To our knowledge, the impact of infrastructure on female LPFR in India has only been researched in the context of village transportation infrastructure. A 2019 study focuses on the impact of road installation on agricultural and non-agricultural employment in a randomly selected group of rural villages (Lei, Desai, and Vanneman, 2019). Lei, Desai, and Vanneman's methodology addresses gender-based differences in LFPR changes, but it fails to address the role of safety in transportation decisions. Findings from this study do support the fact that women are less likely than men to have access to motorized private transport options and spend more time traveling to find work. While this is somewhat useful, the 2SLS model implemented by Lei, Desai, and Vanneman only addresses the question of women entering the workforce, rather than shifts in employment decisions for already working women. Furthermore, similar to the study in Peru (Martinez 2018), this study focuses on general transportation infrastructure rather than gender-specific infrastructure in an urban context.

While previous studies provide a helpful view of the relationships between employment, travel, and infrastructure in various contexts, there are still quite a few factors that demand additional research. In addition to some of the methodological deficiencies identified above, we found no study that examined the impact of gender-specific infrastructure. The Ladies Special is a unique concept in that it provides no functional change for men while transforming commute opportunities for women. Since we are studying the specific effects of a policy explicitly implemented to increase safety on public transportation, our analysis will yield more accurate results about the relationship between employment, safety, and transportation infrastructure. Instead of using potentially weak instruments like Lei, Desai, and Vanneman (2019), we plan to use panel data with two-way fixed effects to study this effect. In regards to why we choose to focus on the city of Mumbai, we believe it poses a generalizable environment to study these changes.

III. Background

The population of the Mumbai metropolitan area is roughly twenty million, with the city proper itself containing roughly 12.5 million residents ("Mumbai Statistics", 2022). The city's railway infrastructure can be explained using the major three lines that carry all travelers from the inner city to peripheral suburbs. The Indian Railways operates the Central, Western, and Harbor lines and operates trains that operate during peak work commute hours. Approximately 7.5 million people in the metropolitan area report using the trains at least once a month, and during peak hours, they are filled to (on average) 2.6 times their intended capacity ("Mumbai Statistics", 2022).

The Ladies Special was started in Mumbai in July of 2009 (Ridge, 2009). To be specific, these trains were fully reserved for female travelers and intentionally timed for peak hours in which crowding issues would be most severe. The program was initiated by the Indian Railways's first female director in response to complaints about harassment and sexual violence in the railway system (Ridge, 2009). Trains were converted to Ladies Specials in the Western and Central Railway lines—but not the Harbour line. The Harbour line only received a dedicated Ladies Special in 2015. They were specifically timed from 7:00 AM to 10:00 AM in the mornings and 5:00 PM to 7:00 PM in the evenings in order to accommodate women traveling for work.

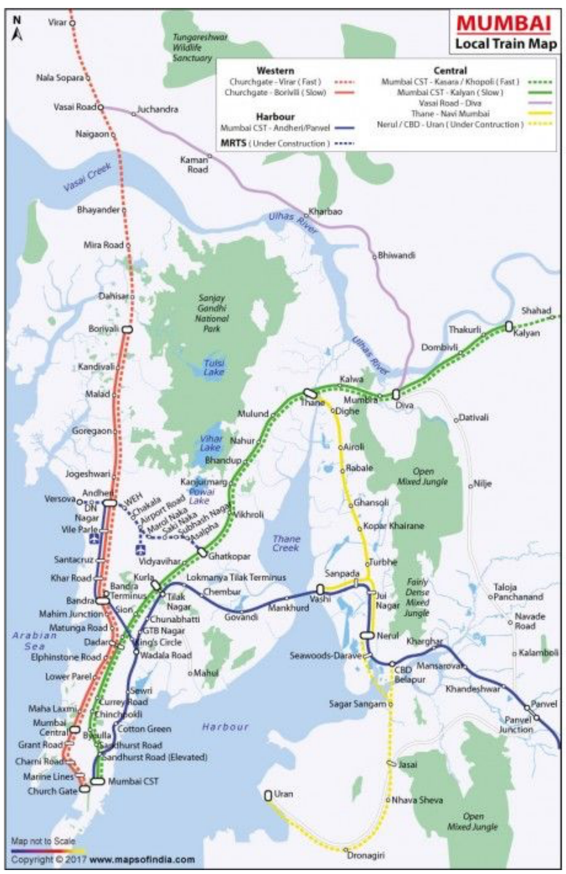
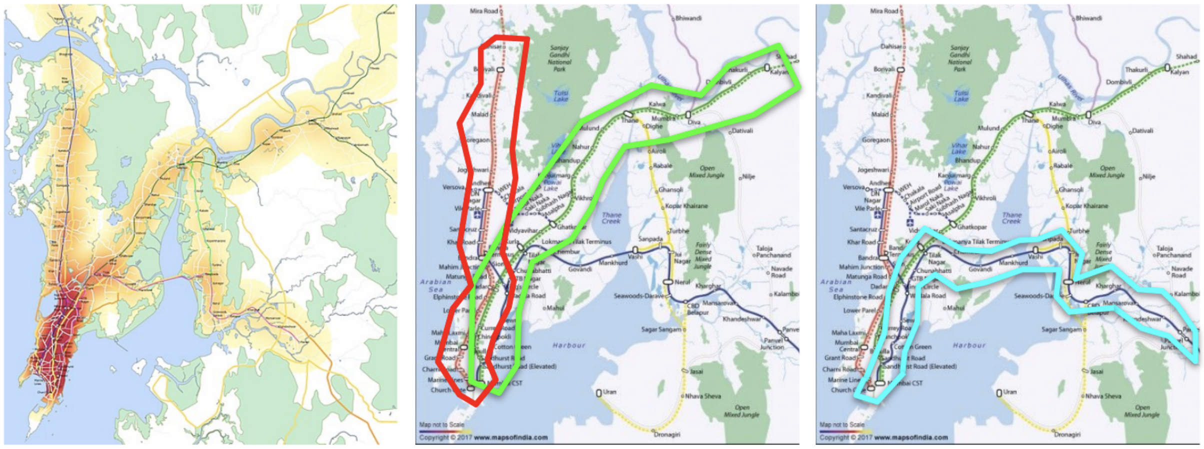


Figure 1A: Major Train Lines in Mumbai

This paper uses the proximity from a Ladies Special train line to identify a causal relationship between labor force participation and access to safe transportation. The cross-sectional comparison of women living near a Ladies Special train line and women living near a non-Ladies Special train line will not be enough to disentangle the existing effect of travel preferences between women living along these two train lines. To address this, we take advantage of the periods before and after the 2009 policy change. Hence, in addition to the cross-sectional comparison of women living near a railway line with and without a women-only train, we can examine the second difference between women traveling on public transportation before the Ladies Special installation and those traveling after.

To explore this variation around the 2009 introduction of women-only trains, we look at women living in neighborhoods along Mumbai train lines between 2006 and 2011. While the Central and Harbor Railway lines converge as they approach the city center and terminate at the same stop, the Western Railway train ends in a different section of Mumbai. Thus, even though the Western Railway also received a Ladies Special train in 2009, we will focus primarily on collecting data from women living along the Central Railway as our treatment group and Harbor Railway as our control group. Figure 1B also shows the train and station density along these two lines, revealing similarities that help confirm our parallel trend assumptions. A census-based GIS analysis in Mumbai finds that both the Central and Harbour Railways service a variety of neighborhoods with similar economic backgrounds and densities (Ramsankaran, 2018). All of these similarities lead us to believe that these are comparable groups for our analysis and excellent opportunities to discover heterogeneity in response to the inception of the Ladies Special in 2009.



Local Train and Station Density | Received Ladies' Special in 2009 | Received Ladies' Special in 2015

Figure 1B: Map of Major Train Lines in Mumbai.[1]

IV. Empirical Strategy:

The first research question we hope to answer asks whether women-only train cars drive female labor force participation. The basic idea behind the identification strategy can be illustrated using a simple differences-in-differences regression. The differences-in-differences strategy relies on the parallel trends assumption which argues that, in the absence of the introduction of the Ladies Special trains, women living in villages along the Central and Harbor Railway lines would have experienced the same trend in labor force participation. We estimate the simple differences-in-differences using the following regression equation:

$$LFP_{it} = \beta_0 + \beta_1 TREATMENT_i + \beta_2 POST_t + \beta_3 TREATMENT_i * POST_t + \varepsilon_i$$

where $TREATMENT_i$ is a dummy indicating whether the woman lives along the Ladies Special train line, and $POST_t$ is a dummy indicating whether the Ladies Special has been introduced

[1] The map of Local Train and Station density shows that access to transportation is concentrated in Mumbai's city center. The Western, Central, and Harbor lines are labeled in red, green, and blue, respectively.

(2009 or later). The outcome variable, LFP_{it}, is a dummy representing whether woman i is participating in the labor force in year t. We define labor force participation to include individuals who are "unemployed and seeking employment" since looking for a job implies that an individual is actively pursuing opportunities which may involve using public transportation to travel away from home.[2] Table 1 more clearly shows how the estimated causal effect of the women-only train cars, β_3, can be obtained as a set of cross-sectional and temporal differences.

	Pre (Before 2009)	Post (After 2009)	Difference
Villages along Central Line (Treatment)	$\beta_0+\beta_1$	$\beta_0+\beta_1+\beta_2+\beta_3$	$\beta_2+\beta_3$
Villages along Harbor Line (Control)	β_0	$\beta_0+\beta_2$	β_2
Difference	β_1	$\beta_1+\beta_3$	β_3

Table 1: Simple Differences-in-Differences Table

To make the parallel trends assumption even more believable, we plan on doing a pre-trend falsification test. Since we have data from 2006 to 2009, we can calculate the yearly labor force participation rate (number of women employed or actively looking for a job/sample size) for our treatment and control villages. By plotting out the trends in a time-sequence manner, we can then observe whether the treatment villages were experiencing the same trend in labor force participation as the control villages prior to 2009. Furthermore, we plan to improve our simple specification by adding a set of control variables such as years of education and village fixed effects:

[2] This specification also aligns with the standard definition of labor force participation. India's National Statistical Office (NSO) defines the labor force participation rate as "the percentage of the population that is either working or actively looking for work". See "Periodic Labour Force Survey" (2022) for more details.

$$LFP_{it} = \beta_0 + \beta_1 TREATMENT_i + \beta_2 POST_t + \beta_3 TREATMENT_i * POST_t + EDU_i + \delta_i + \varepsilon_i$$

These control variables will help reduce standard errors and increase the power of statistical tests.

We expect that the installation of women-only train cars did not have an immediate effect on women's choices to pursue employment opportunities. Since women-only train cars were new to India as a whole, it is unlikely that women immediately believed that traveling on public transportation was safer with the Ladies Specials. Thus, obtaining panel data will allow us to measure how women's employment status changed across multiple time periods. Panel data is also useful because it allows us to control for many time-invariant factors that would be difficult to measure. Existing sources of employment data from the National Sample Surveys and India Human Development Surveys are not consistently available during our time period of interest (Desai et al., 2005).[3] To obtain accurate samples of the population, we will collect survey data from households living fewer than 5 kilometers away from the Central and Harbor Railways. We discuss the data collection process further in the following section.

With panel data, we can estimate a two-way fixed effects model that includes both unit fixed effects and time fixed effects:

$$LFP_{it} = \alpha_i + \gamma_t + \beta_1 TREATMENT_{it} + \varepsilon_{it}$$

where α_i are individual fixed effects, γ_t are year fixed effects, and $Treatment_{it}$ is a dummy variable which represents whether the woman lives near a Ladies Special train line. By including

[3] The India Human Development Survey (IHDS) data interviewed households from 2004-2005 and 2011-2012. While this survey contains useful data about employment surrounding our time range, we found only 585 labeled cases from Mumbai.

individual and year fixed effects, we are effectively controlling for unobserved variation within a person as well as variation across time.

Our second question asks: did the Ladies Special trains have more dramatic effects on women with certain characteristics, particularly education? Generally, we may expect that access to Ladies Special trains may open up more opportunities for women with a college degree than women without a college education. Thus, while women-only train cars may lead to improvements in perceived risk of safety for all women, their use may have differing effects on labor force participation for women with or without college degrees. Furthermore, even if the perceived risk of safety is still high, we may see that more women with college degrees use the women-only trains to join the labor force due to higher opportunity costs than women without college degrees. To estimate these heterogeneous effects we use the following regression equation:

$$LFP_i = \alpha_i + \gamma_t + \beta_1 TREATMENT_{it} + \beta_2 COLLEGE\ EDU_i * TREATMENT_{it} + \varepsilon_{it}$$

where we add an interaction between a dummy variable $COLLEGE\ EDU_i$ which represents whether or not woman i has a college education, and $TREATMENT_{it}$, whether woman i lives near a Ladies Special train line at time t.

V. Data

We plan on conducting a retrospective employment history survey. We are interested in surveying women in their working ages in the control and treatment villages from 2006 to 2012. India's working ages are from 15 to 54. To avoid incomplete survey results (i.e., a woman may be too young to work before 2009 or have retired by the time the trains were introduced, and so only be able to fill out half the survey), we will focus on women who were 18 to 51 in 2009 or 31 to 64 in present day. By doing so, we hope to piece together employment data pre- and post- the introduction of Ladies Special for our difference-in-difference strategy.

Outcome Variables

Our primary response of interest is labor force participation status (=1 if employed or actively looking for a job, = 0 otherwise). We plan on obtaining this information by asking survey respondents to check the option best describing their labor force participation status year-by-year (fig. 2A). Even though 2006 was 16 years ago, we believe that people should have a rough idea of whether or not they were employed on a year-to-year basis.

Additionally, we will ask survey respondents to recall the following things about their employment: job title, industry, and monthly salary. We are interested in these things because on top of just getting women to work, the introduction of the trains might have motivated women who were already working to pursue higher-earning jobs or jobs in different industries. We believe that the most efficient way for us to obtain this information is to ask survey respondents to list their employment history job-by-job (fig. 2B).

We separated labor force participation status and employment details into two sections in the survey for two reasons. First, since labor force participation takes into account whether the person was actively looking for a job, it is hard for us to combine it with employment details in the survey. Second, we hope to use the two sections to cross-validate on the accuracy of people's responses. We anticipate that recall bias will be a major source of measurement error as we are asking people to remember things from more than a decade ago. To mitigate this issue, we plan to look for inconsistencies in people's responses in the two sections and drop observations that are inconsistent. For example, if a survey respondent says that she was employed in 2008 but does not list a job history that corresponds to the year 2008, it is likely that one of the answers is inaccurate.

Another way that we plan to deal with recall bias is to ask survey respondents to indicate how certain they are about their answers ("On a scale of 1 to 5, how certain are you about the information that you have provided for this year/job?"). With this information, we can always opt to drop observations that are very uncertain.

Labor Force Participation

To the best of your ability, please recall your labor force participation status from 2006 to 2012 and check the option that best describes you:

Year	Employed	Unemployed but actively looking for a job	Employed and not actively looking for a job	On a scale of 1 to 5, how certain are you about the information that you have provided for this year (1 is very uncertain and 5 is totally certain)?
2006				1 2 3 4 5
2007				1 2 3 4 5
2008				1 2 3 4 5
2009				1 2 3 4 5
2010				1 2 3 4 5
2011				1 2 3 4 5
2012				1 2 3 4 5

Figure 2A: Survey Section on Labor Force Participation

Employment History

To the best of your ability, please list your employment history from 2006 to 2012:

☐ I had no employment history from 2006 to 2012.

Job 1
Job title: _______
Industry: _______
Estimated beginning and ending years:_______-_______
Estimated monthly salary (INR):_______

On a scale of 1 to 5, how certain are you about the information that you have provided for this job (1 is very uncertain and 5 is totally certain)?
1 2 3 4 5

Job 2
…

Job 3
…

Figure 2B: Survey Section on Employment History

<u>Sample</u>

To estimate an appropriate sample size, we looked at the sample sizes used by previous similar studies. In the 2018 study referenced in literature review, Borker used a dataset containing survey results from 4,000 University of Delhi students to estimate the effect of street harassment on women's education choices in Delhi. The University of Delhi has colleges across Delhi and based on maps created by the author, the distribution of surveys covered about ⅓ of Delhi. Given how Delhi and Mumbai compare in terms of population size (19 million vs. 21 million), our area of interest (roughly one-third of Mumbai), and the population of interest (college students vs. working women), we believe that we should aim for a sample size of around 6,000.

Our main concern with sampling is migration. It is likely that people who were living in the control and treatment villages 16 years ago have moved away or that people who are currently living there came after the introduction of the train cars. Because of this, we cannot just survey people who live in the villages now. Instead, we must identify people who were living in the villages from 2006 to 2012 and survey them. To achieve this in a cost-effective manner, we plan on first working with village representatives to identify individuals who have been living there for a long time and survey these people. If this does not give us a sufficiently large sample supposedly because a lot of people have moved away, we would then try to track down the people who moved away Since we foresee having to deal with issues related to migration in the data analysis stage, we will also ask survey respondents to recall their residential history (fig. 2C).

Residential History

Current village of residence: _______

To the best of your ability, please list the villages that you have lived in from 2006 to 2012:

Village 1
Village name: _______
Estimated beginning and ending years_______-_______

Village 2
...

Village 3
...

Figure 2C: Survey Section on Residential History

Data for Controls and Heterogenous Effects

To collect data on what we plan on controlling for in our regressions (e.g., individual-fixed effects and village-fixed effects), we will ask survey respondents to answer some basic information questions (fig. 3D). We will also collect data on factors that we think could be helpful for investigating heterogeneous effects (e.g., education backgrounds, marital status, whether or not have children, etc.).

Basic Information

Age: _______
Marital status: _______
Number of children: _______

Highest level of education attained:

- ☐ Elementary school
- ☐ Secondary school
- ☐ College
- ☐ Graduate school
- ☐ None of the above

Figure 3D: Survey Section on Basic Information

VI. Conclusion

Our study has the potential to impact policy that can transform India's working-women population. We plan to answer two major questions. First, do women-only train cars improve safety in transportation and consequently lead to increases in female labor force participation? And second, how do the characteristics of these women—particularly their educational attainment—impact the choices they make? These are questions that have yet to be explored by extant research but could reveal important opportunities for developing nations that suffer from gender imbalances. To answer these questions, we plan to use the 2009 introduction of a Ladies Special train line in Mumbai as a natural experiment and analyze the effects through a differences-in-differences approach. By conducting our own retrospective survey, we can collect employment, education, and other individual-level data that is better-suited than existing census data.

As explained in our review of previous research, women in India still continue to make decisions on labor force participation and education on the basis of perceived safety while traveling. Our proposed research is policy-relevant because it can identify a solution that will increase female labor force participation rates at low cost to administrative bodies in the transport system. Creating gender-specific transportation does not necessarily require any new construction, but it could potentially result in many women entering the workforce. Identifying the effectiveness of Ladies Specials is pivotal to not only increasing the prevalence of these specific rail programs but can also extend to other public transit methods. As for extrapolation, the range of economic and educational backgrounds covered by this survey would help clarify how women respond to Ladies Specials in urban settings across India. Even if the results were primarily utilized for the city of Mumbai, the city's large population and economic importance to India makes this low-cost research both imperative and valuable.

VII. Quasi Budget

Item	Cost	Purpose
Traveling and living expenses	$5,000	We need to travel from village to village to coordinate with village representatives.
Printing and mailing	$7,500	We plan on conducting the survey in a written format via email and mail. We estimate that each survey will cost ~$0.5 to print and ~$1 to mail (5000 surveys in total).
Hiring research assistants	$7,500	We plan on hiring 2-3 research assistants to help with the process of conducting the survey (sending out the surveys, asking individuals to complete the survey by phone, collecting the surveys sent back, etc.).
Total	$20,000	

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