Mobility Shocks and Employment Outcomes during COVID-19

Yash Khaitan Shagun Khetan Rohan Wagle

Ashoka University

Abstract

This paper studies the impact of lockdown-induced mobility shocks during the COVID-19 pandemic on employment outcomes in India. Using an individual-level panel from the Consumer Pyramids Household Survey (CPHS) merged with district-level mobility measures from Google Community Mobility Reports, we exploit cross-district variation in reductions in workplace mobility during the national lockdown as a measure of treatment intensity in a difference-in-differences framework with individual and time fixed effects. We find that while average effects on employment are modest, there is substantial heterogeneity: negative effects are concentrated among individuals in the lowest income quartile and among self-employed and salaried workers. We also document significant gender differences, with adverse effects for women but no statistically significant effects for men at the extensive margin. Decomposing employment dynamics, we show that these effects are driven primarily by an increase in job exits and a decline in job entry, with exit effects being substantially larger in magnitude. Overall, the results highlight the unequal labor market consequences of pandemic-induced mobility restrictions across socioeconomic groups.

JEL Classification: J21, J22, J16, O15, I18

Keywords: COVID-19, mobility shocks, employment, gender, labor supply

1 Research Question

How did lockdown-induced variation in mobility during the COVID-19 pandemic affect employment outcomes, and how did these effects vary across gender, wealth, and occupation?

2 Motivation

The COVID-19 pandemic and the subsequent nationwide lockdown in India represented one of the most severe disruptions to global labor markets in modern history. While the health consequences of the pandemic were immediate, economic effects were largely driven by mobility restrictions that limited access to workplaces. In India, income generation is closely tied to physical presence because of a large informal sector and limited scope for remote work. As a result, aggregate employment trends conceal important variation.

Negative employment outcomes are acute for individuals at the middle and lower ends of the income distribution. These individuals largely lack the digital flexibility of high-income professionals and formal safety nets to weather a prolonged displacement from work. Income-based vulnerability often interacts with household labor allocation strategies. When a mobility shock restricts an earner's access to work, households may attempt to reallocate the supply of labour among members to smooth consumption. This may manifest as a gendered division of the shock's burden, where women may disproportionately absorb increased domestic responsibilities or face higher systemic barriers to re-entry into the labour force when mobility is constrained.

Demographic disparities are mirrored in different industries and occupations. On one hand, mobility shocks trigger an immediate surge in job exits as firms in non-essential, site-specific sectors are forced to suspend operations or reduce headcount. On the other hand, the shock prompts a broader paralysis in hiring. The inability to get new staff on board reduces the probability of starting new positions. Although essential sectors or remote-capable occupations provide a buffer, a significant portion of the workforce remains tied to manual or service-oriented tasks.

Using district-level variation in mobility measures, our study aims to identify which populations and sectors bore the highest burden of these disruptions. Such an analysis is critical for understanding whether mobility shocks result in temporary or enduring effects.

3 Literature Review

The literature on the labour market impacts of COVID-19 has evolved from aggregate national assessments to granular demographic and spatial analyses. Initial studies on the Indian labor market during the pandemic, such as Deshpande (2020) and Abraham et al. (2022), utilized CPHS data to document a sharp initial collapse in employment followed by a fragmented and unequal recovery. These studies highlight that the crisis fell disproportionately on women, exacerbating pre-existing gender gaps in both paid and unpaid work. Our findings confirm this gendered impact and shift the focus from the ”pandemic period” to the ”mobility shock” as our primary explanatory variable, allowing for a more precise identification of our proposed mechanisms.

The use of high-frequency digital data to track economic activity has become a cornerstone of recent econometric work. Hoshi et al. (2021) introduced the use of Google Community Mobility Reports to evaluate the effectiveness and costs of non-pharmaceutical interventions (NPIs). While their work focuses on developed economies like Japan, we adapt this framework to the Indian context.

Mongey et al. (2021) establish that workers in roles with low remote-ability and high social-distancing costs bear the disproportionate burden of pandemic-related disruptions. This is further supported by the work of Dingel and Neiman (2020), who categorize the feasibility of working from home across different sectors. Our study applies this logic to the Indian context, where we examine how these occupational and industry-specific constraints determine labor market outcomes. While existing literature largely focuses on job losses (exits) in site-specific sectors, we also investigate the simultaneous paralysis in hiring (entry).

4 Data

Our analysis relies on two primary data sources. The first being the Consumer Pyramids Household Survey (CPHS) conducted by the Centre for Monitoring Indian Economy (CMIE), which is a nationally representative, high-frequency household panel survey covering demographic characteristics, employment status, and income information at the individual and household level. Households are surveyed in rotating panels at regular intervals, with separate modules reporting demographic characteristics, employment status, and detailed income information for individuals and households. We use two of their modules: People of India and Income Pyramids, to obtain information on employment status, industry of occupation, hours worked, individual level demographic characteristics along with individual and household income.

The second data source is the Google Community Mobility Reports[1], which provide district-level aggregated daily information on location activity for individuals who have enabled location history on their Google accounts. The dataset reports mobility patterns across categories such as workplaces, retail and recreation, parks, transit stations, groceries and pharmacies, and residential areas. For the purpose of this analysis, we focus on workplace mobility, defined as the percentage change in visits to workplaces relative to a pre-COVID baseline period, where the baseline corresponds to the median value for the same day of the week during the five-week period from January 3 to February 6, 2020.

To construct our panel, we begin by addressing comparability between the two underlying data sources. A concern is that the mobility data may over-represent younger, urban, and higher-income individuals, as it is based on smartphone users with location tracking enabled. To account for this, we restrict the CPHS sample to regions classified as urban by CPHS, thereby aligning the sample more closely with the population captured in the mobility data. Additional since the mobility measures reflect *changes* relative to a pre-pandemic baseline rather than absolute levels, concerns about representativeness are partially alleviated.

Following this restriction, we construct a district-level measure of the lockdown shock using the Google mobility data. Specifically, we define the shock as the average change in workplace mobility during the nationwide lockdown period from March 25 to May 14, 2020[2]. To ensure that the measure reflects economically meaningful variation in labor market activity, we exclude weekend observations when computing the shock, as mobility patterns on weekends are systematically different and less informative about workplace activity. This results in a time-invariant, cross-sectional measure of lockdown intensity at the district level.

On the CPHS side, we construct an individual-level panel using the People of India and Member Income modules. We focus on a balanced panel of individuals who are observed in all survey waves over the study period and have valid responses, thereby ensuring consistency in tracking employment outcomes over time[3]. Income information is aggregated to the wave level, and we use total income within a wave to account for potential missing observations within months. The district-level shock is then merged to the individual panel using district and state identifiers.

Finally, we apply a set of sample restrictions to ensure consistency of the analysis. We drop individuals who are recorded as having emigrated at any point during the sample period, as changes in employment status for such individuals may reflect geographic mobility rather than labor market

[1]This data has been extensively used for COVID-19 mobility analysis (eg. Hoshi et al. (2021))

[2]Higher values correspond to larger reductions in workplace mobility (i.e., more severe lockdown exposure).

[3]We restrict attention to a balanced panel of individuals observed in all survey waves with valid responses to mitigate concerns about endogenous attrition. In particular, individuals may drop out of the survey following the lockdown for reasons correlated with the shock, which could bias estimates if not addressed.

dynamics. We also restrict attention to working-age individuals and exclude observations with missing employment information. Along with that, districts that have no reliable mobility data are excluded from the final sample.

The final dataset consists of an individual-level panel spanning 2017-2024, where the unit of observation is an individual observed at the CPHS wave level.

5 Empirical Strategy and Results

5.1 Extensive Margin: Employment

We estimate the impact of lockdown-induced mobility shocks on employment using the following difference-in-differences specification[4]:

$$Emp_{idt} = \beta(Shock_d \times Post_t) + \gamma X_{idt} + \eta_i + \delta_t + \varepsilon_{idt} \quad (1)$$

where Emp_{it} is an indicator for whether individual i is employed at time t, $Shock_d$[5] captures district-level variation in mobility, and $Post_t$ indicates the post-lockdown period[6]. X_{it} includes education controls, η_i are individual fixed effects, and δ_t are time fixed effects. This specification exploits cross-district variation in mobility shocks while controlling for time-invariant individual heterogeneity and aggregate time trends. Since the mobility shock is measured as a continuous variable, the coefficient represents the change in employment probability associated with a one-unit increase in the shock. To provide economically meaningful interpretation, we scale coefficients using the mean shock of 50.3, which reflects the typical magnitude of mobility disruption experienced across districts during the lockdown.

Table 1 reports the baseline estimates. The pooled extensive-margin estimates in columns (1) and (2) are negative but not statistically significant. Columns (3) and (4) reports the results of the baseline specification separately for men and women. Evaluated at the mean district-level shock, the estimated effect for women corresponds to a decline in employment of approximately 4.16 percentage points[7]. The corresponding estimate for men is smaller and statistically insignificant. However, the difference in coefficients across genders is not statistically significant (p = 0.454)[8],

[4]All specifications use survey weights and district-clustered standard errors.

[5]The script reverses the original sign (replace shock = -shock), so larger values correspond to larger adverse mobility disruptions.

[6]May 2020 onwards

[7]At the *median* district level shock, the effect is a 3.97 percentage point decline.

[8]We obtain this result by estimating a specification for the pooled sample with an interaction term for differential gender effects.

implying that we cannot reject equality of effects between men and women.

Table 1: Effect of Mobility Shock on Employment

	Pooled		Female	Male
	(1)	(2)	(3)	(4)
Shock × Post	-0.00053	-0.00056	-0.00083*	-0.00024
	(0.00038)	(0.00036)	(0.00040)	(0.00051)
Controls		✓	✓	✓
Observations	102,746	102,746	50,824	51,922

Standard errors clustered at the distrit level in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

To examine distributional impacts, we estimate the baseline specification separately across income quartiles[9]. Table 2 reports the results for each group. For poorer households (Q1), the implied effect at the mean district-level shock is a decline in employment of approximately 9.47 percentage points (9.02 percentage points at the median shock), which is substantially larger than in higher income quartiles where the estimated effects are close to zero.[10] This gradient indicates that mobility shocks are highly regressive in their impact, disproportionately affecting poorer households who may be more reliant on physical presence for income generation and may have fewer opportunities for remote work.

Table 2: Effect of Shock by HH Income Quartile

	(1) Quartile 1	(2) Quartile 2	(3) Quartile 3	(4) Quartile 4
Shock × Post	-0.00188***	-0.000120	-0.000186	-0.0000922
	(0.000713)	(0.000433)	(0.000598)	(0.000454)
Observations	25722	26092	25541	25391

Standard errors clustered at the district level in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

To explore differences across different types of employment, we estimate the model separately for occupation categories: not working, casual labour, self-employed, and salaried workers[11]. Table 3 presents the results for this regression. Evaluated at the mean district-level shock,

[9] Quartiles are calculated on the basis of baseline distribution of household income.

[10] Mean shock $= 50.3958$, median shock $= 48.0263$, range $[21.263, 82.316]$.

[11] Occupation categories are constructed from the CPHS *nature_of_occupation* variable as follows: (i) Not working includes Home Maker, Unoccupied, and Retired/Aged; (ii) Casual labour includes Wage Labourer, Agricultural

employment declines by approximately 2.07 percentage points for self-employed workers and 4.94 percentage points for salaried workers. The estimated effect for casual labour is negative but not statistically significant, while there is no detectable effect for individuals already out of the labour force.

Table 3: Effect of Mobility Shock by Occupation Group

	(1) Not working	(2) Casual labor	(3) Self-employed	(4) Salaried
Shock × Post	-0.00001 (0.00001)	-0.00025 (0.00031)	-0.00041** (0.00018)	-0.00098** (0.00049)
Observations	52,430	14,067	19,787	8,227

Standard errors clustered at the district level in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We further examine labour market dynamics by estimating the effect of mobility shocks on entry and exit probabilities using the following linear probability model:

$$Y_{idt} = \beta(Shock_d \times Post_t) + \gamma X_{idt} + \eta_i + \delta_t + \varepsilon_{idt} \tag{2}$$

Y_{it} represents either exit or entry. Exit is defined as being employed at time $t-1$ and unemployed at time t, while entry is defined as being unemployed at time $t-1$ and employed at time t.

Table 4: Effect of Mobility Shock on Entry and Exit

	Exit (1)	Entry (2)
Shock × Post	0.00090*** (0.00030)	-0.00030* (0.00020)
Observations	47,169	50,097

Standard errors clustered at the district level in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

The probability of transitions in Table 4 indicate that mobility shocks affect employment primarily through increased job separations rather than reduced job creation. Evaluated at the mean

Labourer, Industrial Workers, and Home-based Worker; (iii) Self-employed includes Businessman, Self Employed Entrepreneur, and Small Trader/Hawker; and (iv) Salaried workers include Support Staff, White Collar Clerical Employees, White-Collar Professional Employees, Managers, and Non-Industrial Technical Employees.

district-level shock, the probability of job exit rises by approximately 4.41 percentage points, while the probability of job entry declines by about 1.51 percentage points.

This asymmetry suggests that the immediate impact of mobility restrictions operates through the disruption of ongoing employment relationships where firms are more likely to terminate or suspend existing jobs when faced with constraints on physical operations. In contrast, although hiring activity does decline, the magnitude of this effect is substantially smaller, indicating that the contraction in labour demand is driven more by separations than by a reduction in new job creation.

We assess the validity of the identification strategy using an event study framework (Figure 1 and 2). The results show no evidence of differential pre-trends across districts, supporting the parallel trends assumption. Following the onset of the lockdown, the estimated effects become negative and statistically significant, and persist for approximately four survey waves before gradually attenuating. This pattern indicates that mobility shocks have immediate but not fully permanent effects on employment.

5.2 Intensive Margin: Wage Effects

To examine effects on the intensive margin, we estimate our DiD specification on wages instead of employment indicators. We estimate the following specification only on individuals who are employed at time t:

$$\text{asinh}(\text{Wage})_{idt} = \beta(\text{Shock}_d \times \text{Post}_t) + \gamma \text{X}_{idt} + \eta_i + \delta_t + \varepsilon_{idt} \tag{3}$$

where Wage_{idt} denotes earnings from employment for individual i in district d at time t. Table 5 reports the results. Column (1) presents the pooled estimate, indicating that, conditional on being employed, exposure to the mean district-level mobility shock reduces wages by approximately 17.63 percent.

Columns (2) and (3) report estimates separately by gender. For women, the implied effect at the mean shock is a substantial decline of about 50.39 percent[12]. For men, the corresponding effect is smaller, with wages declining by approximately 16.12 percent at the mean shock.

These findings suggest that mobility shocks not only reduce employment but also lead to substantial income losses among those who remain employed, indicating significant intensive margin adjustment. The larger magnitude of the estimated effect for women points to potentially greater vulnerability in terms of earnings, consistent with constraints such as reduced hours, shifts into

[12] There are only 3,775 employed females in the sample.

lower-paying work, or weaker bargaining power during periods of restricted mobility. However, given the smaller sample size for employed women, these estimates should be interpreted with caution.

Table 5: Effect of Mobility Shock on Wages (Intensive Margin)

	(1) Pooled	(2) Female	(3) Male
Shock × Post	-0.0035**	-0.0100***	-0.0032*
	(0.0016)	(0.0035)	(0.0016)
Observations	39,186	3,226	35,960

Standard errors clustered at the district level in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

We also estimate equation 3 separately by occupation group. The results are reported in Table 6. We find statistically significant effects for farmers and casual laborers (columns (1) and (4)), both of whom experience substantial wage declines following the shock. Evaluated at the mean district-level shock, these correspond to reductions of approximately 13.5 percent for farmers and 52.41 percent for casual laborers.

These results suggest that mobility shocks have pronounced effects on earnings among workers in more vulnerable and less secure forms of employment. In particular, the large decline for casual laborers is consistent with the highly flexible and informal nature of such work, where earnings are closely tied to daily labor demand and hours worked. The negative effects for farmers may reflect disruptions to input markets, supply chains, and the ability to sell produce during periods of restricted mobility.

Table 6: Effect of Mobility Shock on Wages by Occupation Group

	(1) Casual labor	(2) Self-employed	(3) Salaried	(4) Farming
Shock × Post	-0.00268*	-0.00259	-0.00196	-0.0104*
	(0.00148)	(0.00229)	(0.00159)	(0.00526)
Observations	13553	10657	7989	414

Standard errors clustered at the district level in parentheses
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Overall, our results highlight three key patterns. First, while aggregate employment effects are small, substantial heterogeneity exists across income groups, gender, and occupation. Second, labour market adjustment occurs primarily through increased job exits and reduced entry. Third, both employment and wages decline disproportionately for vulnerable groups, particularly low-income individuals and women.

6 Robustness Checks

We re-estimate all key extensive- and intensive-margin specifications without individual FE (using district and wave FE instead). The main conclusions are unchanged. On the extensive margin, the adverse effects remain concentrated among women, low-income households, and self-employed/salaried workers[13]. On the intensive margin, the pooled and female wage effects remain strongly negative and close in magnitude[14]. This suggests that the core pattern is not an artifact of within-person identification alone.

Additionally, as a robustness check, we re-estimate our key specifications using the full unbalanced panel, allowing individuals to enter and exit the sample across waves. This relaxes the balanced panel restriction and addresses concerns that attrition may bias our results if individuals dropping out of the survey are systematically more affected by the shock. The results remain highly consistent with our baseline findings. The coefficient on the mobility shock remains negative and statistically significant across specifications; in our preferred model, the estimate of 0.00069 ($p < 0.01$) implies that a district experiencing the mean shock of 50.3 sees a decline in employment of approximately 3.5 pp.

The heterogeneity patterns are also broadly preserved. The negative effects of mobility shocks are observed across all income quartiles, with magnitudes ranging from roughly 2 to 3.5 percentage points at the mean shock, suggesting that the contraction in employment is not limited to a single segment of the income distribution. Similarly, the effects remain negative and significant for both men and women, with somewhat larger point estimates for women, though the difference is not statistically significant. Across occupations, the adverse effects continue to be concentrated among salaried, self-employed, and casual workers, with little to no impact on those outside the labor force or in farming. Taken together, these results confirm that our findings are robust to relaxing the balanced panel restriction and strengthen the external validity of our conclusions.

[13](e.g., female employment: -0.000798^{*} without individual FE vs -0.000826^{**} with individual FE; Q1 employment: -0.001603^{*} vs -0.001878^{**})

[14](pooled: -0.0032^{*} vs -0.0035^{**}; female: -0.0107^{***} vs -0.0100^{***})

7 Conclusion

Our paper provides a granular analysis of how localized mobility shocks during the COVID-19 pandemic reshaped employment outcomes in India. By exploiting cross-district variation in workplace movement through a difference-in-differences framework, we demonstrate that the economic burden of the lockdown was not borne uniformly.

Our findings reveal that individuals in the lowest income quartile faced the most severe employment losses, likely due to a lack of digital flexibility and limited access to formal safety nets. Furthermore, we document a gendered dimension to the shock. Women experienced a 4.16 percentage point decline in employment at the mean shock level, whereas the effects for men were statistically insignificant at the extensive margin. On the intensive margin, wage compression was substantial, with women experiencing a disproportionate decline of approximately 50.39% at the mean shock compared to 16.12% for men.

A key contribution of this study is the decomposition of labor market dynamics into entry and exit probabilities. We show that the observed employment contractions were driven primarily by a surge in job exits (+4.41 pp) rather than solely by a paralysis in hiring (-1.50 pp). This suggests that mobility restrictions acted as a structural barrier, triggering immediate displacement for workers in site-specific occupations, such as salaried and self-employed individuals.

In conclusion, our research emphasizes that pandemic-induced mobility restrictions do more than temporarily pause economic activity. They interact with technical and institutional constraints to exacerbate pre-existing inequalities. For vulnerable groups, particularly women and low-income earners, these transitory shocks may translate into long-term labor market effects. These results underscore the need for targeted policy interventions that account for occupational proximity and household labor allocation strategies to mitigate the socioeconomic consequences of future disruptions.

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Appendix

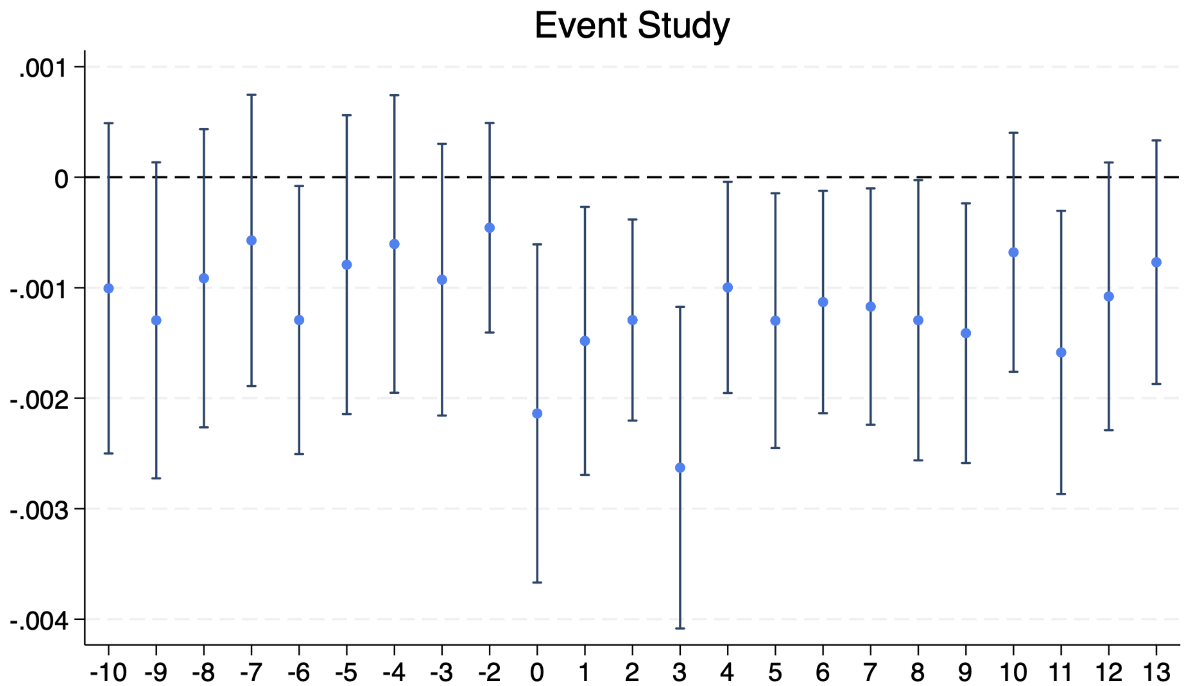

Figure 1: Dynamic Effects: Extensive Margin (Balanced Panel)

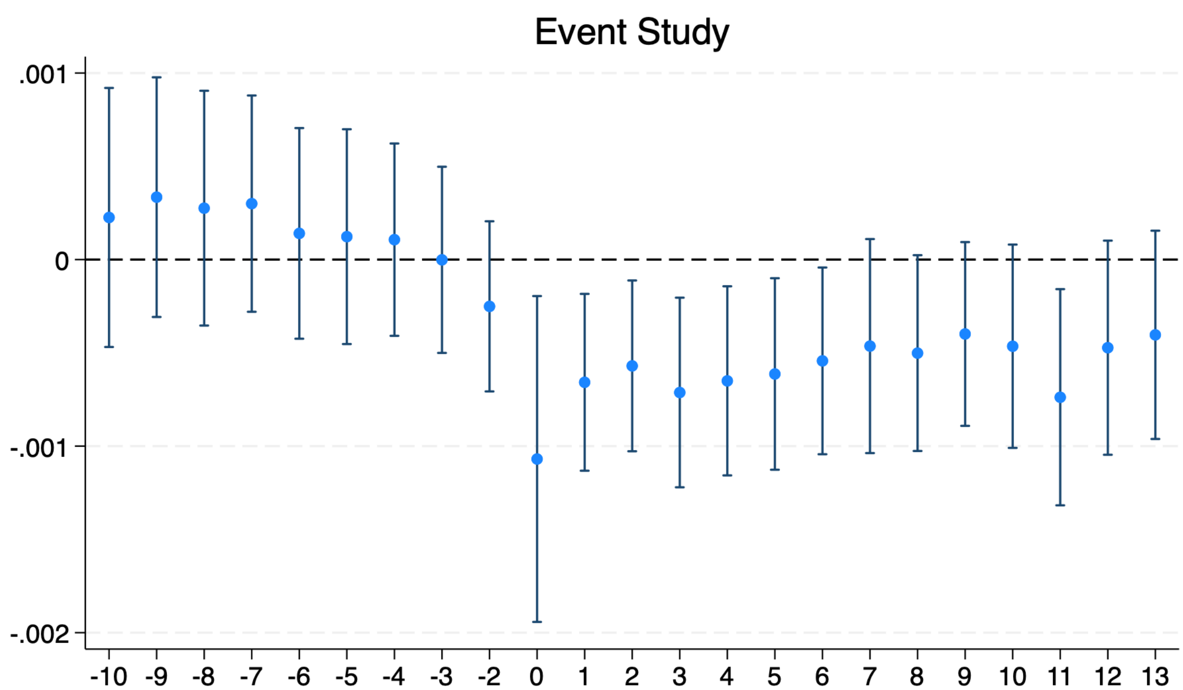

Figure 2: Dynamic Effects: Extensive Margin (Unbalanced Panel)