Youth Responses to Household Income Shocks in Informal Labor Markets: Evidence from Brazil

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Abstract

In a country where informal employment is the primary outside option for youth and more than half of college entrants drop out before completing their degrees, a sudden income shock—such as parental job loss—can significantly alter their job search behavior and college attendance. Little is known about how young people respond to such negative shocks in high-informality settings. This paper examines this question using a difference-in-differences approach and a large panel dataset that captures both formal and informal employment and tracks youth–parent pairs for one year. I show that parental job loss increases youth labor force participation by 24%, with nearly all of this adjustment occurring through informal jobs and a smaller share through self-employment, and that this increase in labor activity persists a year after the shock. At the same time, college persistence declines by about 10%, driven by exits from private institutions, while public university enrollment eventually recovers over time. No statistically significant effects are found among youth from higher-income households, with adjustments concentrated among youth likely serving as informal insurance within financially constrained families.

Keywords: parental job loss, youth labor supply, informal employment, college enrollment, developing countries

JEL Codes: J13, J24, J46, J64, I25, O15

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1 Introduction

In a country where almost 60% of youth work in the informal sector and over half of college entrants drop out before completing their degrees, household income shocks can significantly influence young people's decisions related to work and education. Similar vulnerabilities are present across many developing countries, especially those experiencing rapid demographic growth (Bandiera et al., 2022).[1] While a growing literature examines the effects of positive income transfers on youth outcomes (Blattman et al., 2014; Machado et al., 2025), evidence on how youth respond to large *negative* income shocks remains limited—despite these being far more common. This issue is especially relevant in contexts where families have limited access to formal insurance mechanisms to smooth consumption (Corado et al., 2024): even short-term income losses can push young individuals into early labor market entry or lower-quality jobs, with potential long-term consequences for human capital accumulation.

This paper provides the first causal evidence on how parental job loss affects youth labor market behavior and college attendance in a developing country with high informality. Using data from the Continuous National Household Sample Survey (PNADC)—one of the world's largest quarterly household surveys in Brazil, covering both formal and informal employment—I construct a panel of over two million youth matched to their parents over the period 2012–2019. The empirical strategy leverages variation in the timing of parental job loss events within a staggered difference-in-differences framework, employing estimators robust to treatment effect heterogeneity (Callaway and Sant'Anna, 2021). The identifying assumptions are supported by flat pre-trends across all outcomes and stable estimates under increasingly restrictive sample definitions.

The results show that parental job loss leads to a statistically significant increase in youth labor supply. On average, labor force participation rises by 10.1 percentage points in the four quarters following displacement, corresponding to a 24% increase relative to the baseline mean. This effect is concentrated on the extensive margin: youth who were previously out of the labor force enter it. Earnings and hours worked also respond positively, with average increases of 15%, and the consistency of results across different labor market measures mitigates concerns about measurement error.

To shed light on the quality of youth employment following parental job loss, I examine the type of jobs they undertake. The increase in youth labor supply is concentrated in informal em-

[1] Bandiera et al. (2022) project that by 2050, one in three people starting to look for their first job will be born in Africa, underscoring the relevance of studying disadvantaged youth (15–24 years) and their job search behavior.

ployment, particularly in unregistered jobs without formal contracts. Formal employment rises more gradually, and self-employment remains largely unaffected. Importantly, the employment response varies by the age at which the shock occurs: younger individuals (14–20) are more likely to enter informal work, while older youth (21–24) are more likely to access formal jobs. This heterogeneity underscores that the timing of exposure to a financial shock matters for the quality of employment outcomes. These patterns are consistent with standard job search models in dual labor markets, where a negative income shock lowers reservation wages and increases search effort, and where informal job offers arrive at higher rates for young workers (Finamor, 2024). Crucially, recent evidence shows that informal employment is not a stepping stone to better jobs: Donovan et al. (2023) document that workers in developing countries cycle through marginal employment without progressing, and Abel et al. (2022) show that while informal jobs may pay more at entry, formal wages grow substantially faster. The transition into informality is thus not a neutral detour—it places young workers on a flatter earnings trajectory at the stage of life when the returns to human capital investment are highest.

I also examine the effects on higher education. Parental job loss leads to a decline of approximately 10% in college attendance among youth aged 18 to 24. Disaggregating by institution type reveals that the decline is concentrated among students in private universities, where attendance drops persistently within one year of the shock, while attendance in public universities—which are tuition-free—falls temporarily but recovers. This asymmetry is consistent with a liquidity mechanism: the constraint is financial, not motivational. The finding contrasts sharply with Hilger (2016), who finds no effect of parental job loss on college attendance in the U.S., attributing this to generous federal grant and loan programs. In Brazil, where no equivalent program exists for this age group, the effects of parental income shocks on higher education are substantial.[2]

The results point to household income loss as the primary mechanism driving youth responses. Parental earnings drop sharply upon separation and remain approximately 60% below pre-shock levels one year later—consistent with patterns observed in studies using administrative data (Britto et al., 2022). When estimating effects by pre-displacement income, significant behavioral responses are concentrated among youth in the bottom of the distribution, while effects at the top are small and statistically indistinguishable from zero. In a setting where formal insurance is limited, these findings suggest that low-income households face heightened liquidity constraints following displacement. Youth appear to take on an informal insurance role: they increase labor market participation and, in some cases, reduce college attendance to help buffer

[2]The Pé de Meia program, targeted at secondary school students, was introduced only in 2024.

the household against income loss.

The main results are robust to a series of specification checks, including reweighting by propensity scores using the doubly robust estimator, incorporating a rich set of covariates, relaxing the requirement that the partner remains employed, and restricting the control group to the not-yet-treated.

Related Literature. This paper contributes to the empirical literature examining the impact of parental job loss on children's outcomes. Most studies in this area focus on developed countries—particularly the United States and Scandinavian countries—and emphasize educational indicators such as grade repetition (Rege et al., 2011), or long-term outcomes like children's future earnings (Oreopoulos et al., 2008; Hilger, 2016). College attendance has been studied almost exclusively in the U.S., primarily by Hilger (2016), who finds no significant effects among low-income students—a result attributed to the availability of generous student aid programs. Fradkin et al. (2019) is the only study analyzing youth labor market responses—focusing on Belgium—and similarly reports no significant effect on job quality, and only a modest increase in total days worked three years after displacement.

To the best of my knowledge, this is the first study to estimate the causal effect of parental job loss on youth labor market outcomes and higher education in a low- or middle-income country. While a small but growing literature has examined the consequences of parental displacement in this context, existing studies focus predominantly on younger children and on other outcomes. Fontes et al. (2024), using a comparable identification strategy, draws on mental health survey data to examine the impact of parental job loss on Brazilian children aged 6–12, and finds a 24% increase in the probability of a mental disorder diagnosis. Di Maio and Nisticò (2019) study children aged 10–16 in Palestine using quarterly household survey data, finding that parental job loss increases the probability of school dropout by 9 percentage points. GC Britto et al. (2023) also focus on early educational outcomes for children aged 9–16, using large-scale administrative data from Brazil, and find increases in school dropout and age-grade distortion of up to 1 and 2 percentage points, respectively.[3]

This paper differs from the existing literature by focusing on youth outcomes, particularly labor market behavior and higher education enrollment—two margins that are especially salient

[3]Before these recent contributions, additional studies have examined correlations between parental employment status and children's outcomes without explicitly addressing endogeneity. Skoufias and Parker (2006) find a negative association between parental job loss and school attendance for girls during the Mexican peso crisis. Duryea et al. (2007) show that during economic crises in Brazil, father's job loss is correlated with higher school dropout rates among children. Oliveira et al. (2014) focuses on youth aged 14–20 and examines the correlation between parental transitions into inactivity or unemployment and youth labor supply, finding a positive correlation.

in a context of high informality. Young people in this age group (14–24) are at a critical juncture where they begin making autonomous decisions about employment and education, yet many remain financially dependent on their families. There is no major nationwide cash transfer program targeted at youth in this age group.[4] As a result, household income shocks may strongly influence their behavior. Notably, the strong responsiveness observed here contrasts with the limited or null effects reported by Hilger (2016) in the U.S. for low-income families.[5]

Furthermore, this paper provides empirical evidence for a mechanism that is well established in theory but has not been tested: the effect of negative income shocks on youth acceptance of informal employment. Search models with dual labor markets predict that income-constrained workers lower their reservation wage and accept the first available offer, which in developing countries is disproportionately informal (Finamor, 2024). A large empirical literature has studied how *positive* interventions—cash transfers (Machado et al., 2025), vocational training (Attanasio et al., 2011; Alfonsi et al., 2020), job search assistance (Abebe et al., 2021; Bandiera et al., 2023), and temporary wage incentives (Abel et al., 2022)—shape youth employment outcomes. While these studies typically examine positive shocks, this paper contributes by documenting how youth respond to a *negative* income shock, providing novel evidence on the asymmetry of behavioral responses.

Finally, this paper contributes to the literature on the added worker effect. Halla et al. (2020) provide the leading causal evidence that spousal labor supply responds to job displacement. I document a parallel mechanism for youth, which carries distinct welfare implications: unlike spousal adjustments that primarily redistribute current income, youth labor supply responses alter the trajectory of human capital accumulation during the period when the returns to investment are highest.

2 Institutional Context

Brazil is the largest country in Latin America and ranks as the 7th largest in the world, with a population of 211 million. Despite possessing the 8th largest GDP worldwide, Brazil is still considered a developing country, ranking 89th in the Human Development Index (HDI) and approximately 80th in GDP per capita. Furthermore, Brazil remains one of the most unequal countries globally, demonstrated by a Gini Index of 53.4 in 2020.

[4]The Pé de Meia program, introduced in 2024, targets secondary school students.

[5]The research design is further supported by evidence from the Brazilian labor market showing that results are remarkably similar whether job loss is defined broadly or restricted to mass layoffs (Bhalotra et al., 2025; Britto et al., 2022; GC Britto et al., 2023).

There are key elements to consider when analyzing the Brazilian labor market: high levels of informality, turnover, and the cost of job loss. Additionally, young people entering the workforce face a different labor market than adults, with higher rates of informality, unemployment, and earlier school-to-work transitions. Therefore, this section is divided into two subsections: one on the Brazilian labor market in general and another more specific on the youth labor market in Brazil.

2.1 Brazilian Labor Market

Formal employees in Brazil are protected by the *Consolidação das Leis do Trabalho* (CLT), which mandates that each employer must fill out and sign the employment record of their employees upon hiring. According to *Relação Anual de Informações Sociais* (RAIS) 2017, 94% of all contracts in the private sector are full-time and of indefinite term. The most common forms of termination for these jobs are layoffs without cause (i.e., involuntary job loss), accounting for 70% of all cases.[6]

In Brazil, firms have the freedom to dismiss employees without cause, although they must pay compensation. In particular, formal employees are entitled to a paid 'advance notice' of at least one month, a severance payment, and 3 to 5 months of unemployment insurance. The severance payment corresponds to up to 40% of the balance of the worker's linked account in the *Fundo de Garantia do Tempo de Serviço* (FGTS), managed by the employer with proportional monthly deposits.[7] The notice period and the unemployment insurance duration depend on the employee's tenure and total contribution time.[8] After these benefits end, the only additional form of income support at the national level is *Bolsa Família*, a well-known conditional cash transfer focused on families in extreme poverty.

Despite the Brazilian labor law being very restrictive with high dismissal costs, Brazil exhibits one of the highest labor turnover rates in the world by some comparable measures. Gonzaga et al. (2003) shows that in the 1990s and early 2000s, the annual turnover rate was approximately 40%, one of the highest among countries with available data. Since then, the turnover rate has not declined, and da Rocha et al. (2019) shows that estimates for 2013 indicate the continuation

[6]The second-largest cause of termination is voluntary resignation, accounting for 17%, followed by contract expiration, at 11%. Dismissals with cause—known as *justa causa*—comprise only 2% of the reasons.

[7]Under the FGTS regime, each company in Brazil must deposit 8.5% of their active formal employees' salaries in accounts opened in the name of each worker in a state-owned bank.

[8]An employee who accumulated 6, 12, or 24 months of contributions across all formal jobs in the 36 months prior to dismissal is entitled to 3, 4, or 5 months of unemployment insurance, respectively, if unable to find another position. Additionally, the worker must not have received unemployment insurance benefits for another termination in the past 16 months.

of a high level at 50%. In a more recent study, Britto et al. (2022) also highlighted the unstable nature of employment in Brazil. In their analysis of a broad and representative sample of formal workers, 37% of dismissals happened in the first year of employment.

The Brazilian labor market is largely characterized by high informality. According to the *Pesquisa Nacional por Amostra de Domicílios Contínua* (PNADC from now on), in 2017, the workforce consisted of approximately 104 million people, of which 40% held informal jobs. Although informality is extensive, it can constitute an imperfect self-insurance for displaced workers (Ponczek and Ulyssea, 2020). However, studies such as those by Engbom et al. (2022), Donovan et al. (2023) and Gomes et al. (2020) show that workers transitioning from formal to informal employment face a significant reduction in earnings, along with greater income instability. Furthermore, Gerard and Gonzaga (2021) demonstrates that the transition to the formal market is slow: 94% of workers receiving unemployment benefits remain without formal employment four months after dismissal, and 50% continue without formal relocation after a year.

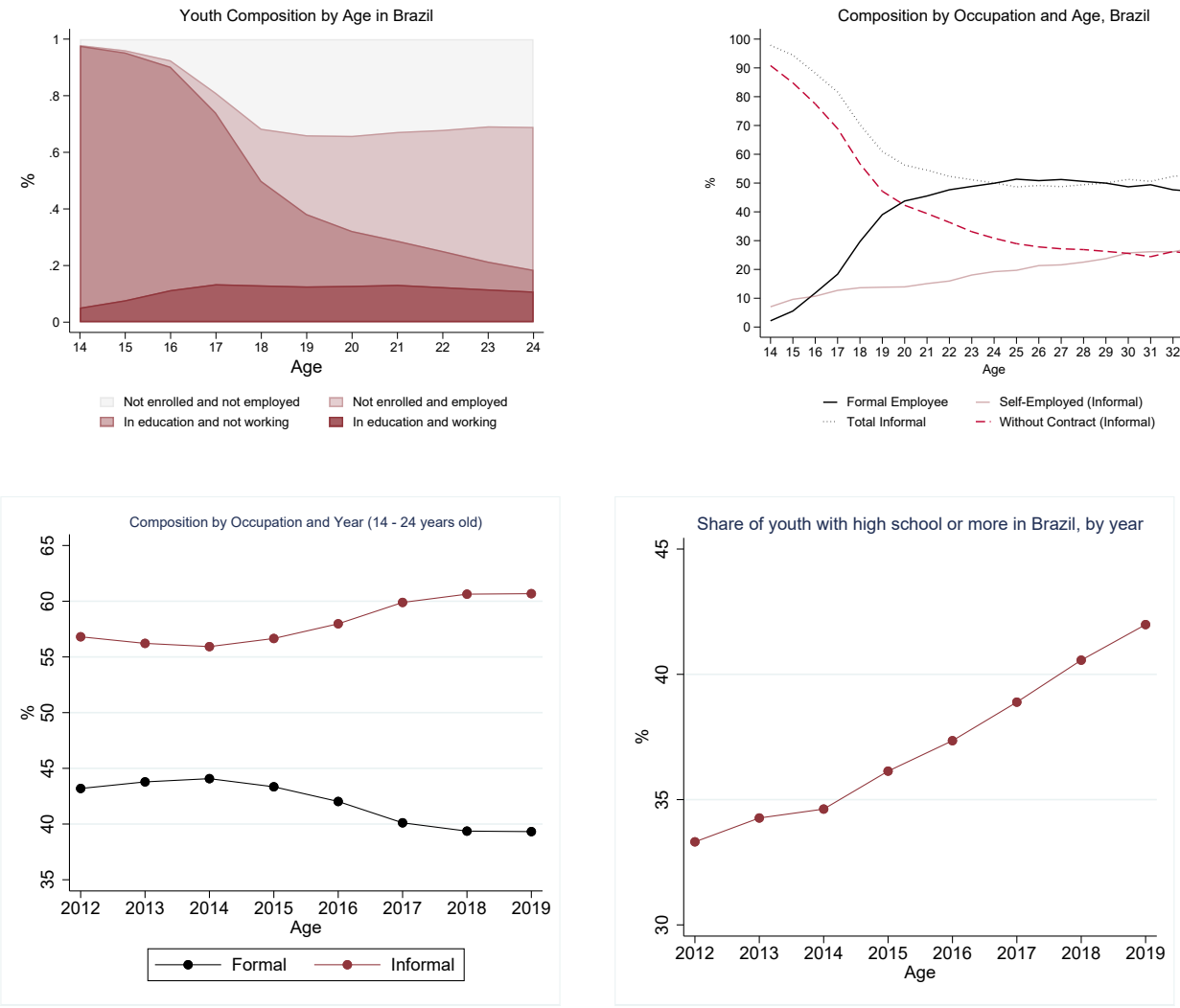
In the Brazilian context, job loss can have lasting effects not only on employability but also on credit and consumption. In a recent contribution for Brazil, Corado et al. (2024) shows that displaced workers experience a 20% reduction in credit card limits, which limits their options for self-insurance. Furthermore, individual consumption decreases by 26% following dismissal, and even those who are quickly reemployed do not return to previous patterns. This scenario contrasts with more developed economies such as the United States, where job loss does not affect credit, as demonstrated by Braxton et al. (2024). Similarly, Hilger (2016) shows that parental job loss in the US does not significantly affect children, aligning with the fact that in these countries, the impacts of job loss on credit are minimal. Therefore, in a country where job loss represents a significant shock and private market insurance options are very limited for individuals out of the formal labor market, the need for informal risk-sharing arrangements—such as kinship transfers and peer-to-peer lending—may become more pronounced.

2.2 Youth Labor Market

This section provides an overview of the Brazilian youth labor market, using some aggregate indicators. By OECD standards, Brazil has a relatively youthful workforce, although this is changing rapidly recently. The proportion of youth neither in employment, nor in education or training (NEET) is considerably above the OECD average. Their first jobs are typically precarious: informal employment remains a significant feature of the Brazilian labour market,

and youth employment is characterised by very high turnover and low wages.[9]

Figure 1: Descriptive Statistics on Young People in Brazil



Note:
This figure describes the composition of youth education and employment in Brazil using PNADC data. Informal employment includes both unregistered wage jobs and self-employment. Panel A shows the distribution of youth aged 14 to 24 across four categories: not enrolled and not employed, not enrolled and employed, enrolled and not working, and enrolled and working. Panel B presents the share of youth in each type of job (formal, informal with a contract, and informal without a contract) by age, conditional on being employed. Panel C displays the composition of the youth workforce by sector (formal vs. informal) over time, while Panel D reports the share of youth with at least a high school degree.

The first panel shows that most youth are fully enrolled in education until around age 15. Between ages 16 and 18, however, there is a rapid increase in the share of youth who begin to combine school and work. By age 18—coinciding with the typical age of high school completion—a significant portion has left the education system altogether. This early exit from

[9]For a better review of the youth labor market in Brazil, see Reis (2015), Corseuil et al. (2013), and Brazil (2014).

school is mirrored by a strong increase in labor force participation, particularly in informal employment (Panel B).[10] Strikingly, despite recent gains in educational attainment—reflected in a steady increase in the share of youth with at least a high school diploma between 2012 and 2019—the share of informal employment among young workers has remained persistently high, with around 60% of employed youth aged 14–24 working informally throughout the period.

The composition of the labor market in Brazil varies significantly over the life cycle, with informality prevailing among the young, while formal employment and self-employment gain relevance at older ages. Among workers aged 14 to 17, more than 60% are engaged in the informal sector, which serves as the main entry point into the labor market for this age group. Participation in the formal sector grows with age, surpassing informality around the age of 20, while self-employment, although not very prominent among youth, shows a gradual increase. This dynamic is important for understanding how the interaction between individual economic shocks and labor market structure affects youth depending on their age. In a context without informality, a shock like a parent's job loss could compromise the continuity of education, but the youth would tend to enter the formal market, limiting the long-term negative impacts. However, in a highly informal scenario, this same shock can have an amplified effect: informality, acting as a buffer, facilitates early entry into the labor market, but also creates a rebound effect by exposing young people to low-quality jobs. Thus, the institutional context underscores the importance of considering the age at which the shock occurs, which can intensify the cost of an early and undesirable entry into the labor market. I explore this in more detail in the results section.

The process of labor market insertion for Brazilian youth is characterized by early entry into work, widespread informality, and limited educational attainment. These patterns jointly reflect and reinforce the economic vulnerability of young individuals during the school-to-work transition.

3 Data

The main data source is the PNADC from 2012 to 2019, the largest high-frequency household survey in Brazil, conducted by the Brazilian Statistical Census Bureau (IBGE).[11] The PNADC data is advantageous in our context because it encompasses both the formal and informal sec-

[10] This graph is consistent with the findings by Narita (2020) for the period of 2002–2007 using the Brazilian Labor Force Survey (PNAD).

[11] The PNADC is conducted by the Brazilian Institute of Geography and Statistics (IBGE), a federal agency under the Ministry of Planning and Budget. The PNADC quarterly data is available at the IBGE website and is publicly available through this link.

tors of the economy. This is especially important given the high unemployment rate among individuals aged 14–24, with about 60% of those employed in this age group working in the informal sector (Figure 1), which are not recorded in administrative data by definition. These challenges are especially pronounced when analyzing youth, who are largely outside administrative records—since they are either unemployed or employed informally, they are absent from administrative data by definition.[12] The PNADC is the second-largest quarterly household survey globally in terms of sample size and stands out for its detailed variable coverage (Donovan et al., 2023).[13] The survey adopts a rotating panel scheme of interviews. This means that households are subsequently interviewed for up to five quarters, that is, every two months. In each quarter, about 211,000 households are interviewed, covering approximately 16,000 census sectors of 3,500 municipalities. The rotation scheme of the PNADC is presented in Table 3 in the Appendix.[14]

Although PNADC has a panel structure, IBGE does not provide an individual identifier for longitudinal analysis, only a household identifier. Ribas and Soares (2008) developed an identification algorithm to enhance the quality of individual panel data. In Basic identification, some fixed individual characteristics reported in the survey, as date of birth and gender, are used to identify the same individual in two or more interviews. In Advanced identification, the individuals left without pairing constitute a sample that will be identified by a method that considers the answer's closeness, where small inaccuracies reported in the individual characteristics are permitted to reduce the attrition.[15] To map individuals across surveys and construct an individual-level panel, I use the advanced identification.[16]

Attrition. A concern in my analysis is attrition in the longitudinal sample. The attrition rate in the main sample is approximately 18% by the fifth interview, which is low relative to comparable panel surveys.[17] Throughout this study, I show that individuals with more

[12]Despite these challenges, a growing number of studies in developing countries use survey data to perform causal inference—often through event-study designs—particularly in relation to labor market outcomes. For example, Berniell et al. (2021) uses data from Chile to estimate the dynamic effects of motherhood on women's informal labor supply. Marcos (2023) leverages the timing of grandmothers' deaths in Mexico as a shock to childcare availability to study women's employment. More recently, in Brazil, Fontes et al. (2024) analyzes the effects of parental job loss on children's psychological well-being using mental health survey data.

[13]See Donovan et al. (2023), which compares surveys across 48 countries. Table A3 and Table A6 in the paper.

[14]This 1-2(5) rotation scheme is also used in labor market surveys in countries such as Mexico (*Encuesta Nacional de Ocupación y Empleo* (ENOE)) and the UK (*Labour Force Survey*).

[15]I utilize the DataZoom package, which has adapted the identification algorithm developed by Ribas and Soares (2008) in Stata and R. The Stata code for the PNAD-C algorithm is publicly available and can be accessed here.

[16]Recently, Osorio (2022) introduced new improvements to the PNADC identification algorithm that can be implemented in this work in the future.

[17]For reference, annual attrition rates in the former PME survey averaged around 50% (TEIXEIRA JÚNIOR et al. (2016)), and the U.S. Panel Study of Income Dynamics (PSID) experienced approximately 50% cumulative

vulnerable characteristics are also those most affected by parental job displacement. This pattern suggests that attrition may lead to an underestimation of the treatment effects, as these same individuals are more likely to drop out of the panel over time (see Table 4). Nevertheless, the bias introduced by attrition is likely to be small. As shown in Figure 4 and Figure 13, the observable characteristics of individuals who remain in the sample and those who attrit are relatively similar.

I also test whether attrition differs between treatment and control groups and find no statistically significant difference, suggesting that differential attrition is unlikely to bias the estimates. To interpret the difference-in-differences estimates, I assume that both groups follow similar attrition dynamics and experience comparable patterns of measurement error over time.[18] I also incorporate the non-response weights provided by IBGE in all regressions. I aim to mitigate these limitations through transparency in the presentation of results and by demonstrating strong empirical consistency across alternative specifications and outcome definitions. The estimates should be interpreted as reflecting the average response among a relatively more resilient sample, making it plausible that the true effects of parental job loss may be even stronger among more vulnerable groups.

4 Sample Selection

Step 1: Identifying Parents. I rely on the household identifier and the position of each individual in that household, as Di Maio and Nisticò (2019) and Fradkin et al. (2019) do. Specifically, the children are identified as "the child of the head and the spouse of the household".[19] Parents are thus defined as those individuals registered as *head* or *spouse* within the child's household. While this approach relies on household composition rather than direct information on biological ties, the age distribution of parents in our sample suggests a high degree of accuracy in this identification strategy. On average, mothers in our sample were approximately 25 years old at the birth of their child—closely aligning with official statistics from the 2000 Brazilian Census. The sample's average paternal age at childbirth is 27.85 years, consistent with demographic patterns in which men typically partner with slightly younger women.

Step 2: Identifying Job Loss Shocks. A parent (father or mother) is classified as experiencing

attrition (Fitzgerald et al., 1998). In developing-country panels, Alderman et al. (2001) find that even with substantial per-wave attrition, multivariate estimates of behavioral relationships are not significantly affected.

[18] In the results section, I show that measurement error is unlikely to drive the findings, as estimates remain stable across a range of employment outcomes, including hours worked, earnings, and occupation.

[19] This identification also includes cases in which the individual is the biological child of only one parent (e.g., living with a father and stepmother).

job displacement in quarter T if he or she (i) was employed in the private sector during quarter $T-1$, regardless of whether the employment was registered or unregistered, (ii) was classified as unemployed in quarter T according to IBGE's official definition,[20] and (iii) did not search for another job in the previous quarters.[21] To reduce confounding effects related to retirement decisions, I also restrict the sample to parents aged 25 to 59 years.

The motivation for the selection process is the following. First, condition (i) ensures that individuals categorized as self-employed in $T-1$—approximately 30% of the sample—are not considered in the definition of job displacement. The rationale behind this is that self-employment involves distinct labor market dynamics; transitioning from self-employment to unemployment often reflects business downturns or temporary shocks rather than a job loss. However, as documented by Dal-Ri (2024) using administrative data for formal employment in Brazil, significant effects are observed in cases involving involuntary layoffs followed by transitions to self-employment. Therefore, this definition allows for the possibility that a displaced worker may re-enter the labor force through self-employment a quarter after displacement.

Second, condition (ii) tries to rule out cases such as job-to-job transitions, switches between salaried employment and self-employment, or episodes of inactivity (due to sickness or accident). Van Doornik et al. (2018) documents that such strategic separations are common in Brazil and are typically followed by transitions from formal to informal employment in order to gain access to unemployment insurance. By focusing exclusively on transitions into unemployment, my definition reduces the likelihood of capturing these cases. Third, by focusing on workers not engaged in long job searches prior to displacement, condition (iii) aims to maximize the likelihood that the job loss is unanticipated or unplanned, such as the termination of an employment contract.

Finally, unlike many studies in the job loss literature (e.g. Jacobson et al. (1993) and Couch and Placzek (2010)), I do not impose any restrictions related to tenure when defining job displacement. I follow the approach adopted by recent studies focusing on the Brazilian labor market, which do not apply tenure-based restrictions (e.g., Britto et al. (2022) and Fontes et al. (2024)). This choice is primarily motivated by the high labor market turnover in Brazil. Despite this, I leverage the availability of tenure information in my dataset to conduct robustness checks. Specifically, I re-estimate the main results using subsamples restricted to workers with at least 6, 12, and 24 months of tenure at the time of displacement. The results indicate that the main

[20] This classification requires meeting three criteria during the reference period: (i) not engaged in any form of work; (ii) available to commence employment immediately; and (iii) actively searching for work.

[21] Figure 12 in the Appendix shows the distribution of job search duration for displaced individuals. Over 85% declared having searched for work 0–3 months at the quarter of displacement, lending support to the identifying assumption.

findings remain largely consistent.

Step 3: Defining the Treatment and Control Group. The identification strategy relies on comparing three distinct groups: the treatment group, the not-yet-treated group, and the never-treated group. The *treatment group* consists of youth whose parents were both employed prior to the treatment period, but one parent experiences a job loss while the other remains continuously employed throughout the analysis period. The *not-yet treated group* comprises households that will experience job loss in the future but have not yet been treated during the current observation window. Finally, the *never treated group* includes households in which the parents remain continuously employed throughout the entire observation period.

5 Descriptive Evidence

Figure 14 in the Appendix displays descriptive trends for the two main outcomes: labor supply and college attendance. The graphs show averages for the treatment group across quarters, normalized to quarter -1. Labor supply increases following the shock, while college attendance declines—suggesting behavioral shifts associated with parental displacement. Following practices in the difference-in-differences literature (Baker et al., 2025), I also assess covariate balance both in levels and in pre-treatment trends.

Table 1 displays baseline characteristics for individuals in the treatment and control groups, along with their standardized differences. Most variables exhibit small differences across groups. The only exception is parental age, which slightly exceeds the threshold—not surprising given that younger workers face higher turnover and are therefore more likely to experience job displacement. Figure 15 in the Appendix presents pre-treatment trends in key covariates. The visual evidence supports the parallel trends assumption: pre-treatment covariate changes are flat and similar across groups, with no clear divergence prior to the shock.

6 Methodology

The empirical strategy aims to identify the effects of parental job displacement on youth outcomes over time. To address pre-existing differences in levels and control for common shocks, I use a staggered difference-in-differences framework that leverages the timing of parental job losses for identification. In particular, I rely on Callaway and Sant'Anna (2021)[22] methodology

[22]Recent methodological contributions highlight that a straightforward two-way fixed effects (TWFE) regression is not well suited for causal interpretation in settings with multiple time periods, staggered treatment timing, and heterogeneous treatment effects. TWFE estimators recover a weighted average of underlying treat-

Table 1: Covariate Balance Statistics: Levels

	Control		Treatment		Std. Diff.
	mean	sd	mean	sd	
Parents Characteristics					
——— *Father* ———					
Age	45	(7)	43	(7)	0.26
White	0.38	(0.48)	0.31	(0.46)	0.14
Education (High school or more)	0.34	(0.47)	0.33	(0.47)	0.02
Log Earnings	7.32	(1.02)	7.23	(0.80)	0.10
Hours Worked	42	(12)	41	(11)	0.05
Informal Employment	0.46	(0.50)	0.50	(0.50)	0.07
——— *Mother* ———					
Age	42	(6)	40	(6)	0.23
White	0.38	(0.48)	0.33	(0.46)	0.14
Education (High school or more)	0.43	(0.49)	0.45	(0.50)	0.05
Log Earnings	6.94	(1.05)	6.81	(0.87)	0.13
Hours Worked	34	(14)	34	(13)	0.02
Informal Employment	0.56	(0.50)	0.57	(0.50)	0.02
Children Characteristics					
Age	17	(3)	17	(3)	0.07
White	0.39	(0.48)	0.32	(0.46)	0.15
Gender (Male)	0.50	(0.50)	0.50	(0.50)	0.01
Attends School	0.79	(0.41)	0.79	(0.41)	0.01
Age-grade distortion	0.25	(0.44)	0.26	(0.44)	0.02
Incomplete Elementary	0.35	(0.48)	0.37	(0.48)	0.03
Complete Elementary	0.42	(0.49)	0.43	(0.50)	0.04
Household Characteristics					
Nuclear Family (Man)	0.75	(0.43)	0.66	(0.47)	0.20
One Child	0.46	(0.50)	0.47	(0.50)	0.02
Two Children	0.37	(0.48)	0.36	(0.48)	0.01
Three or More Children	0.18	(0.38)	0.17	(0.38)	0.02
Observations (all Interviews)	596,030		30,940		626,970

Note: Descriptive statistics for pre-treatment covariates by treatment status.

to estimate dynamic treatment effects.

ment effect parameters, but some of these weights may be negative. See Roth et al. (2023), De Chaisemartin and d'Haultfoeuille (2023), and Baker et al. (2022) for recent surveys on this literature.

6.1 Estimation and Aggregation

Let $i \in \{1, 2, \ldots, N\}$ denote observations for young individuals and $t \in \{0, 1, 2, 3, 4\}$ an interview in a particular quarter. Define G_{gi} as a dummy variable equalling one if the parent of individual i was displaced in period g.[23] Let C be a dummy variable equal to 1 for children who are not treated in any period. Finally, let $Y_t(1)$ and $Y_t(0)$ denote the potential outcomes of children's outcomes with and without parental job loss, respectively. The main building block of our framework is the average treatment effect for children who are members of group g at a particular time t, denoted by:

$$ATT(g,t) := \mathbb{E}[Y_t(1) - Y_t(0) \mid G_g = 1] \tag{1}$$

Under some assumptions and for a given treatment *type*, Callaway and Sant'Anna (2021) propose an unconditional estimator for the average treatment effect of parental job loss for cohort g at time $t \geq g$ given by:

$$\widehat{ATT}^{\text{type}}(g,t) = \frac{\sum_i \Delta Y_{i,g-1,t} \mathbf{1}\{G_i^{\text{type}} = g\}}{\sum_i \mathbf{1}\{G_i^{\text{type}} = g\}} - \frac{\sum_i \Delta Y_{i,g-1,t} C_i}{\sum_i C_i} \tag{2}$$

Where $\Delta Y_{i,g-1,t} \equiv Y_{i,t} - Y_{i,g-1}$ is the evolution of outcome Y in a given quarter t relative to the quarter before treatment $g-1$. This estimator is equivalent to a two-period/two-group DD estimator that compares the average outcome evolution of the treated group in year t, post-treatment, relative to year $g-1$, pre-treatment, with the average outcome evolution of the control group across the same periods.

After estimating each $\widehat{ATT}^{\text{type}}(g,t)$, I choose to present the main results in an event-study aggregation, which combines the estimates by relative time since the treatment quarter ($e = t - g \in \{-3, \ldots, 3\}$).[24] To evaluate magnitude and heterogeneities, I combine the post-treatment estimates ($e \in \{0, \ldots, 3\}$) into a single measure. The aggregations of this estimator are weighted by the share of treated individuals in each cohort.

It is also possible to estimate treatment effects in pre-job loss periods to test the plausibility of the underlying parallel trends assumption defining our DID design. Following De Chaisemartin and d'Haultfoeuille (2023) and Callaway and Sant'Anna (2021), for a fixed event-time $e \geq 0$, I use a placebo estimator that replaces the "long comparisons" across $g-1$ and $g+e$ (between

[23] Note that $t = 0$ represents the interview where all parents are employed by design. Therefore, if $g = 1$, treatment occurs between $t = 0$ and $t = 1$; $g = 2$ between $t = 1$ and $t = 2$; and so on. The proportion of parents who report losing their jobs in interviews 2, 3, 4, or 5 are similar.

[24] The options never-treated and not-yet-treated for control group; "short-gaps" for periods before treatment; and method "reg"—outcome regression DiD estimator based on ordinary least squares are selected. See the "csdid.ado" Stata command help file for further information.

groups that switched from untreated to treated at g and those remaining untreated until $g+e$) with "short comparisons" across $g'-1$ and g' for all $g' < g$. Different from TWFE regressions, we do not have a universal baseline period. For each placebo treatment period g', we compare it to the immediately preceding period. In this case, my pretreatment parameters are pseudo-ATTs: they are the treatment effects we would have estimated had the treatment taken place at the placebo date. Estimates of the pre-treatment coefficients using long-differences, reported in the Appendix, are similar to the ones from our baseline specification.[25]

7 Identification

The estimator in Equation 2 relies on three assumptions for identification.

Irreversibility of Treatment. This assumption posits that once units receive treatment, they remain treated throughout the observation period. In my context, this can be interpreted as units not forgetting the treatment experience, regardless of re-employment in subsequent periods. This seems reasonable, as job losses lead to employment and income consequences that are not recovered within the first year (see Figure 2).

No anticipation. The no anticipation assumption implies that treatment effects begin only at the time of the treatment or afterward, but not before. In my context, anticipation effects would likely bias the estimates downward, as children might begin adjusting their labor supply even before their parent's formal job loss. However, as I will show in the results section, there is no clear evidence of such anticipatory behavior. Moreover, the possibility of adjustment during the notice period is limited in the Brazilian labor market, where notice periods are relatively short due to high labor market turnover.[26]

Parallel trends. Parallel trends are needed so we can impute the missing $E[Y_t(0) \mid G_g = 1]$ with $E[Y_t(0) \mid G_g = 0]$ in Equation 2. That means that in the absence of parental job loss, the outcome evolution between $g-1$ and t for treatment cohort g would be the same as the evolution of the control group $C_i = 1$. An advantage of my setting relative to some papers in the literature[27] is that I observe youth labor market outcomes before and after job loss events,

[25] In this case, all our event-study estimates have a similar interpretation. In TWFE regressions, one has to normalize relative to a universal baseline period (generally the period immediately before the treatment starts); otherwise, parameters are not identified due to perfect multicollinearity. Both are valid strategies to pretest the parallel trends assumption.

[26] Usually between 30 and 39 days (for 1 to 3 years of tenure).

[27] In contexts where pre-shock child outcomes are unavailable—such as when job loss occurs during childhood or adolescence—standard event study methods cannot be applied. To address this limitation, the literature relies on a conditional independence assumption, comparing children whose parents experienced job loss due to mass layoffs or plant closures with those whose parents remained employed in stable firms (e.g., Oreopoulos et al. (2008), Bratberg et al. (2008), Rege et al. (2011)). The key identifying assumption is that job loss resulting from

so I can deal with any unobserved reasons for parental job loss that are time-invariant in a DiD framework by checking for pretreatment trends. The effects for pre-treatment periods, which are generally statistically indistinguishable from zero for my primary outcomes, bolster the design validity.

Assessing the Validity of the Research Design. A potential concern is that workers who lose their jobs may differ from those who remain employed in unobserved ways that also affect child outcomes. Indeed, Table 1 shows that, while children in the treatment and control groups appear broadly similar, parents who experience job loss are slightly different from those who do not: they tend to be younger, more likely to be non-white, earn lower wages, and are more often women. The main identification challenge, therefore, lies in the possibility of selection into job loss based on time-varying confounders correlated with child outcomes, which could violate the parallel trends assumption.

To address this issue, some prior studies have focused exclusively on job loss stemming from mass layoffs or plant closures,[28] thereby limiting the scope for endogenous separation. Unfortunately, my data do not contain information on such events. As a result, the job loss measure used here may capture both exogenous and endogenous dismissals.

However, evidence from Brazil suggests that endogeneity concerns in this context may be limited. Recent studies using difference-in-differences designs with rich administrative data from Brazil—examining the impacts of parental job loss on crime, domestic violence, and child educational attainment—find remarkably similar results whether job loss is defined broadly or restricted to mass layoffs or plant closures (Bhalotra et al., 2025; Britto et al., 2022; GC Britto et al., 2023).[29] In Section 8.1, I replicate a standard layoff exercise to estimate the magnitude of labor income loss following job displacement and find effects closely aligned with those reported in the studies cited above. Taken together, these results suggest that, despite the absence of a granular classification of job separations in my data, the risk of bias due to endogenous selection into treatment is likely small.

plant closures is effectively random when controlling for observable characteristics.

[28] While the use of mass layoffs or plant closures as a source of exogenous variation is common in the literature, recent findings suggest that this strategy may not be universally appropriate. For instance, Hilger (2016) warns that focusing solely on firm closures or mass layoffs can introduce bias in the U.S. context, as such events may reflect firm-specific downturns rather than purely exogenous shocks. Instead, he adopts a difference-in-differences design based on individual layoffs and uses propensity-score reweighting of non-laid-off parents and highlights the importance of comparing pre- and post-treatment dynamics to strengthen causal inference.

[29] This interpretation is supported by Brazil's high labor market turnover, as discussed in Section 2, with annual rates exceeding 50% in 2013. In such a context, job separations are more likely to reflect broader structural dynamics rather than unobserved worker characteristics. Fontes et al. (2024) makes a related point. This may help explain why studies using administrative data from Brazil often report similar results regardless of how job loss is defined.

As a robustness check, I also follow Fontes et al. (2024) and leverage the depth of my dataset to employ a propensity score–weighting strategy. This approach balances the treated and control groups across a variety of covariates, thus allowing the assumption of *conditional* parallel trends. These covariates include basic parental and child demographics (such as state of residence, race, age, year, and gender), in addition to parental education and the number of children. By adopting this methodology, I aim to mitigate potential biases that might emerge if labor market outcomes were influenced by these baseline characteristics.

To conduct inference on the estimates from Equation 2 and subsequent aggregations, I rely on the multiplier bootstrap procedure proposed by Callaway and Sant'Anna (2021). In all specifications, standard errors are clustered at the individual level to account for heteroskedasticity and serial correlation within individuals. I also tested clustering at the household level, and the results remain robust.

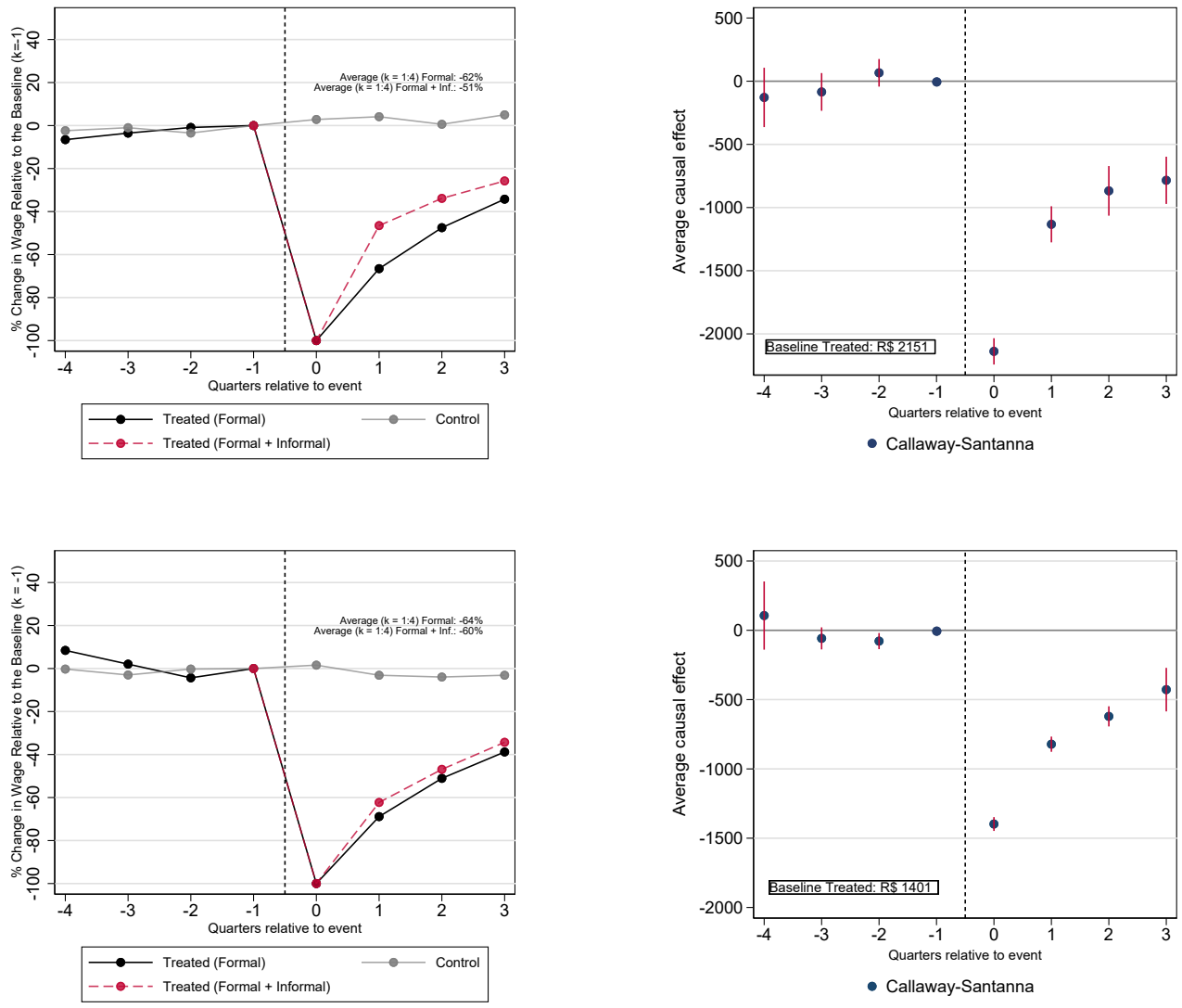
8 Results

8.1 Effect of Job Loss on Parental Labor Income

Before turning to the consequences of parental job loss on youth outcomes, I first show how job loss impacts parental labor income. Extensive research has illustrated that job loss has severe repercussions on individuals' lives.[30] In line with the literature, job loss causes substantial income losses for both mother and father, as shown in the graphs of Figure 2.

[30]See Jacobson et al. (1993); Couch and Placzek (2010); Schmieder et al. (2023); Zimmer (2021) for labor market outcomes. This empirical framework was leveraged in numerous subsequent papers examining the impacts of job loss under various settings, examining effects on mortality (Sullivan and Von Wachter, 2009) and mental health outcomes (Zimmer, 2021). For a review of this growing literature and other outcomes, see Flaaen et al. (2019).

Figure 2: Effect of Job Loss on Parental Labor Income



Note: This figure shows the effect of job loss on formal and informal labor earnings, by parental gender. The left panels display simple averages of the percentage income variation relative to $k = -1$. The right panels present dynamic treatment effects estimated using Equation 2, with 95% confidence intervals. Informal employment is defined as self-employed or workers without a formal labor contract.

The graphs on the left present the simple averages of the relative labor income variation based on the baseline period ($k = -1$). One year after job loss, formal income drops by 62% for fathers and 64% for mothers compared to the control group. These effects are quantitatively similar to the results from previous papers using Brazilian administrative data to track job loss events and formal employment outcomes (e.g., Britto et al. (2022)).[31]

[31]They found a 65% formal labor income drop for men in the first year, while I found 62%. They used a

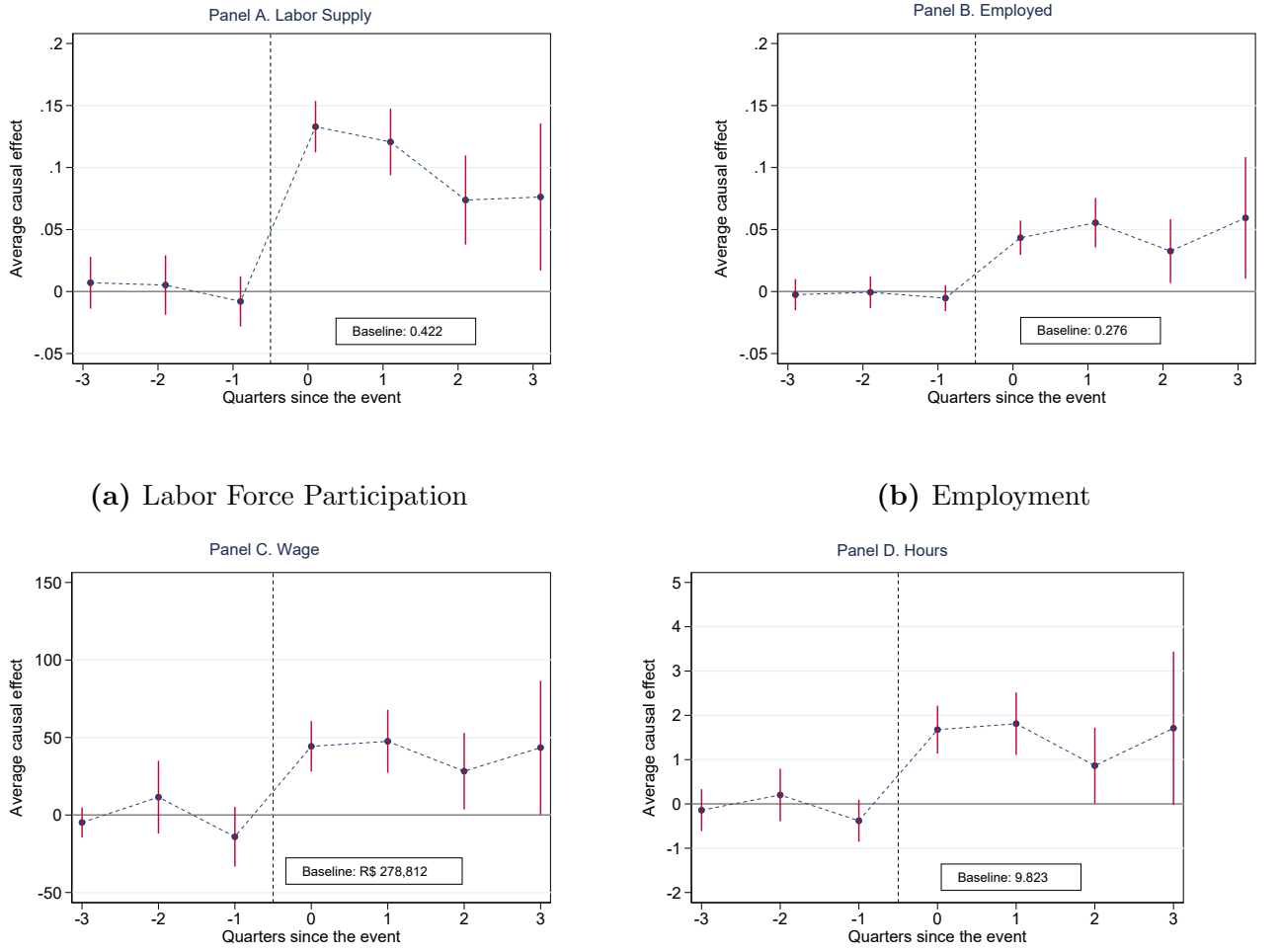
When considering the informal sector, income losses are 51% for fathers and 60% for mothers. This finding is consistent with the role of the informal sector as a buffer against economic shocks (Ponczek and Ulyssea, 2020). The graphs on the right provide a more detailed picture of income dynamics, incorporating a 95% confidence interval and presenting the dynamic treatment effects using the specification in Equation 2. In the pre-treatment period, income trends for treated and control groups were virtually the same. Although there is some income recovery over time, earnings remain below baseline levels one year after displacement. Taken all together, this evidence suggests that job loss appears to be correctly captured in the data: the research design generates large and quasi-experimental variation in parental income across households.

sample of individuals aged 20 to 50 years, while I used individuals aged 25 to 59 years.

8.2 Effect of Parental Job Loss on Youth Labor Market Outcomes

8.2.1 Youth Labor Supply and Employment

Figure 3: Effect of Parental Job Loss on Youth Labor Market Outcomes



(a) Labor Force Participation

(b) Employment

(c) Monthly Earnings

(d) Hours Worked

Note:

Dynamic treatment effects estimated using Equation 2, with 95% confidence intervals. The treatment group consists of youth whose parents transitioned from private-sector employment to unemployment. The control group includes youth whose parents remained continuously employed.

Extensive margin. I now turn to the analysis of youth labor market outcomes, beginning with labor supply.[32] I estimate the event-study specification presented in Equation 2. Panel A of

[32]I have chosen labor force participation as my primary outcome variable for two reasons. First, due to the high unemployment rate for young people in developing countries, focusing solely on employment rates could underestimate the full extent of young individuals' responses to parental job loss. Second, labor force participation allows for the detection of anticipatory effects—that is, whether individuals begin adjusting their behavior before the shock occurs.

Figure 3 shows the effects of parental job loss on youth labor force participation, defined as the sum of employed individuals and those actively searching for work.[33] Prior to the shock, there are no significant differences between the treated and control groups, supporting the common trend assumption. However, in the quarter of the event ($t = 0$), labor force participation rises significantly and remains elevated in subsequent quarters. Table 6 confirms this effect: labor force participation increases by 13.3 percentage points (p.p.) immediately after the shock, with an average effect statistically significant of 10.1 p.p. over the period. Given a baseline participation rate of 42.2%, this represents a 23.9% increase.

Panel B of Figure 3 presents the effects on employment. The increase in employment in the event quarter is 4.3 p.p., with an average effect of 4.8 p.p. over the quarters, representing a 17.3% growth relative to the baseline employment rate of 27.6%. Unlike labor force participation, the impact on employment is smaller, indicating that not all young individuals entering the labor market immediately secure jobs. This is consistent with historically high unemployment rates for youth in this age group in Brazil.[34]

Panels C and D provide further insights by analyzing employment responses through alternative measures: hours worked and earnings. Specifically, Table 6 shows that parental job loss leads to an average increase of R$40.9 in earnings, corresponding to a 14.7% rise relative to the baseline average of R$278.81.[35] The effects on hours worked are of a similar magnitude, with an estimated 15% increase relative to the baseline. The consistency of these results across different employment outcomes mitigates concerns about non-random measurement error.

In the job displacement literature, where job losses are typically identified through major firm events leading to sudden employment drops, it is difficult to account for the anticipation of a worker's own job loss. This is particularly relevant in light of Hendren (2017), who provides evidence from various sources that individuals often have some prior knowledge of their impending job loss. Studying another household member's responses offers a unique opportunity to assess anticipation at the household level. Unlike displaced workers, children are not bound to react at a specific moment; they can begin job searching even before their parent loses employment. Therefore, a key feature in Panel A of Figure 3 is that the gap in youth labor supply rates

[33]Job search is defined according to IBGE's classification, which includes: *(i)* contacting potential employers, *(ii)* participating in or registering for competitive exams, *(iii)* consulting employment agencies, unions, or similar organizations, *(iv)* responding to job advertisements, *(v)* seeking employment through personal networks such as relatives, friends, or colleagues, or through self-advertisement, *(vi)* initiating a self-employment activity by searching for premises, equipment, or fulfilling other prerequisites, or *(vii)* applying for permits or licenses required to operate a business.

[34]The unemployment rate in my sample hovers around 30% for this age group between 2012 and 2019.

[35]For this estimation, I replaced missing values for non-employed individuals with zero in both hours worked and earnings. This explains the relatively low baseline average.

emerges only after parental displacement. This suggests no evidence of anticipatory behavior among children, at least in terms of job search within the observed time frame.

The main analysis restricts the sample to households where the spouse remains employed. Still, results are robust to relaxing this restriction (see Figure 17 in the Appendix). This dynamic may also reflect structural features of the Brazilian labor market. Evidence from Corseuil et al. (2014) shows that young individuals face relatively fewer barriers to hiring and are not close substitutes for adults, making them a more accessible adjustment margin in times of financial stress.[36] In this context, since youth have less experience, they may take on low-paying informal jobs to help stabilize the household income shock, while adults tend to delay reentry in search of better opportunities.

The full event-study estimates are reported in Table 6 in the Appendix.

Intensive Margin. Traditionally, the "added worker effect" refers to non-working household members entering the labor force to compensate for lost income. However, such responses may also arise along the intensive margin—that is, among those already working, adjustments may occur through increased working hours. Halla et al. (2020), for example, examines both the extensive and intensive labor supply responses of wives to their husbands' unemployment, finding that behavioral adjustments can occur not only via labor market entry but also through changes in hours worked or employment intensity. In contrast, little is known about how young individuals, who are often at the margin of labor market entry, respond to similar shocks.

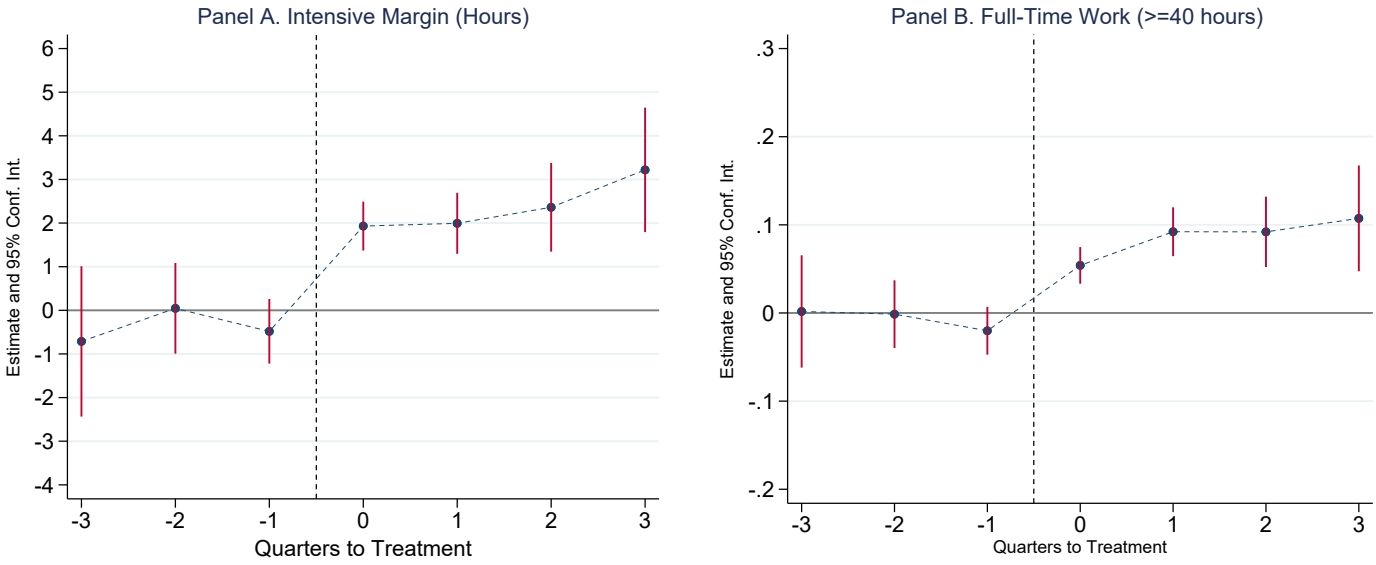
In our context, 26% of youth in the sample were already employed at the time of parental job loss. This allows us to go beyond analyzing market entry and to investigate whether labor supply adjustments also occur at the intensive margin. Specifically, we examine whether previously employed youth increase their working hours or shift toward full-time jobs.

Figure 4 presents an event study analysis of these effects. Before the event, estimated effects fluctuate around zero. At $t = 0$, hours worked increase significantly, indicating a rapid response to the household income shock. Estimates indicate an increase of approximately 3 hours by $t = 3$, representing an 8.8% rise relative to the baseline. There is also a noticeable and sustained increase in the likelihood of full-time work (Panel B), with estimates gradually rising over time. The stronger effect on the extensive margin (23% increase in labor market entry) compared to the intensive margin (8.8% increase in hours worked) suggests that the primary labor supply response occurs through new entrants joining the labor force rather than previously employed youth significantly increasing their hours.

[36] Using administrative data from the formal labor market, the authors find that nine out of ten new hires are youth, compared to only four out of ten among adults. Moreover, substitution between young and adult workers is limited: only 5% of youth job losses are compensated by adult employment.

This pattern reflects the socioeconomic dynamics of households where youth are already employed at an early age. In lower-income families, it is common for young individuals to contribute to household income while balancing work and education. The fact that these youth were already working before the shock suggests that their families may have faced financial constraints even prior to parental job loss and were already close to their feasible working-hour limits, limiting their ability to further expand their labor supply. In contrast, families with previously inactive youth rely more on the extensive margin, as these individuals can more readily enter the labor force to help compensate for the income shock.

Figure 4: Effect of Parental Job Loss on Hours Worked (Intensive Margin)

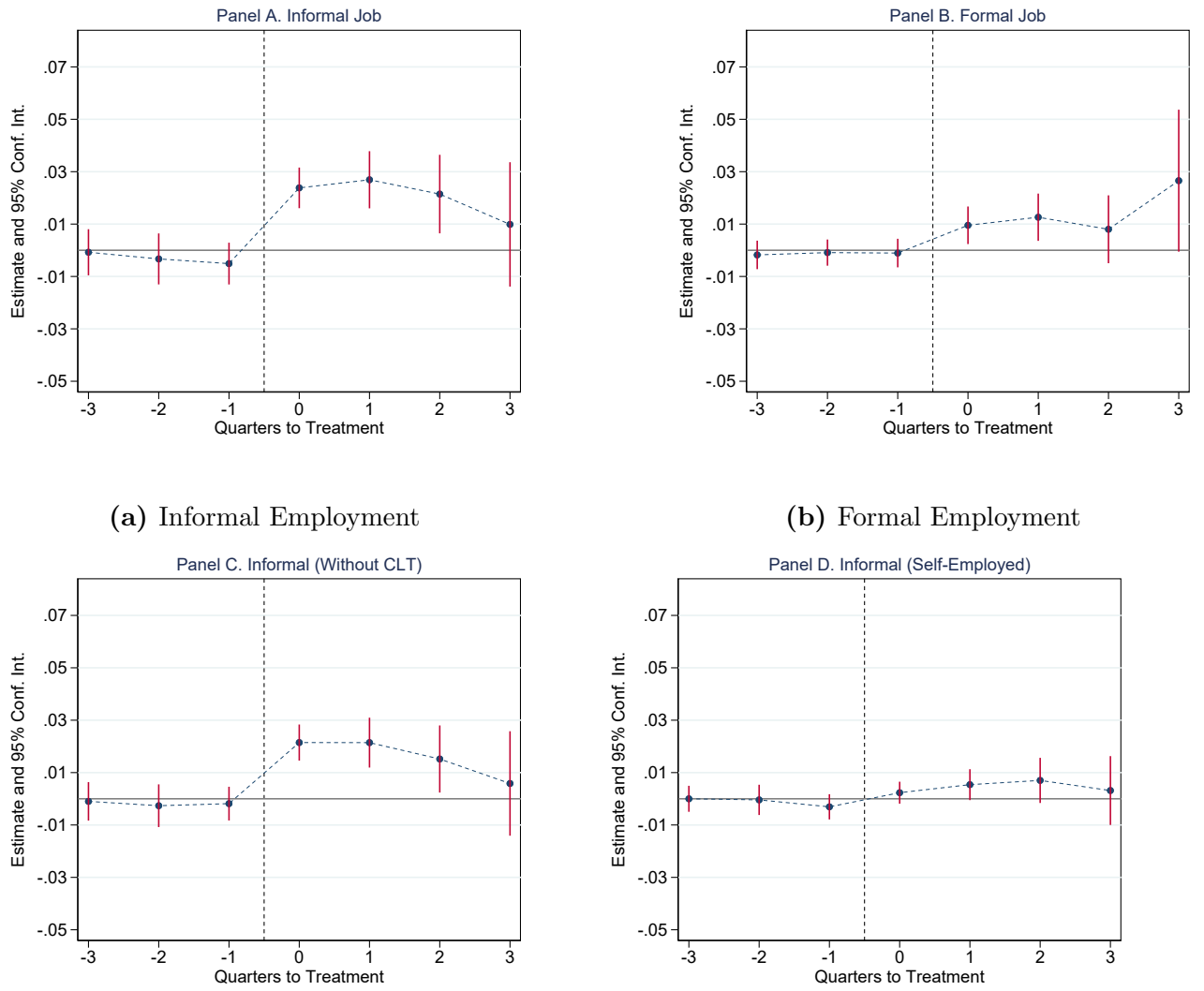


Note: Panel A shows the effect on hours worked conditional on being employed. Panel B shows the effect on the probability of working full-time.

8.3 Youth Informal Employment

The quality of early labor market experiences plays a key role in shaping long-term outcomes. Evidence from developed countries shows that entering the labor market under adverse conditions can have persistent effects on earnings, employment stability, and broader life outcomes (Wachter, 2020). These effects are likely to be even more pronounced in economies like Brazil, where informal employment is widespread. Cruces et al. (2012) shows that cohorts exposed to higher levels of informality in their youth fare systematically worse in the labor markets as adults. Therefore, it is crucial to understand not only if young people increase their work efforts,

but also the types of jobs they undertake. To that end, I examine heterogeneity in employment responses by distinguishing between formal employment, informal work without a contract, and self-employment.



(a) Informal Employment

(b) Formal Employment

(c) Unregistered Jobs

(d) Self-Employment

Note: Dynamic treatment effects of parental job loss on youth employment type, estimated using Equation 2, with 95% confidence intervals. The control group consists of youth whose parents remained continuously employed.

Figure 5: Effect of Parental Job Loss on Youth Employment by Type

Figure 5 shows an immediate rise in informal employment among youth following parental job loss, whereas formal employment increases more gradually over time. Over subsequent quarters, the probability of informal employment declines slightly, while formal employment becomes more common. This may reflect both high turnover in informal jobs and the gradual accumulation of experience that facilitates transitions into formal work. Indeed, some studies suggest that

informal employment can serve as an entry point for youth from disadvantaged backgrounds (Ziss and Dick, 2003). Although evidence on the role of informality among young people is still limited, Reis (2015) highlights that youth without prior work experience face substantial barriers to accessing formal employment, further reinforcing the role of informality as a possible first step into the labor market.

A decomposition of informal employment shows that the entire effect is driven by jobs unregistered. In contrast, self-employment remains largely unaffected. The lack of response in self-employment supports the view that financial constraints and accumulated capital prevent low-income youth from starting their own businesses, consistent with Finamor (2024).

This raises concerns that a forced entry into the informal sector due to a financial shock—especially at a stage critical for professionalization and human capital accumulation—may have lasting effects on youth's future career trajectories. If early exposure to informality limits skill accumulation and restricts access to better jobs, the consequences of entering the labor market under financial distress may extend beyond the short run.

These results suggest that youth may be using the informal sector as a mechanism to absorb household-level economic shocks, such as parental job loss. Informality offers a low-barrier entry point into the labor market, enabling young individuals to respond quickly to sudden income losses. However, while informality may ease short-run adjustment, it often comes at a cost. Informal jobs tend to offer lower wages, no social protection, and limited opportunities for skill development or advancement. For young individuals, early exposure to informal work may hinder human capital accumulation and contribute to persistent labor market disadvantage (Cruces et al., 2012).

Heterogeneity by Age of Shock. How does the age at which parental job loss occurs influence the type of employment pursued by those affected, especially in an environment characterized by high informality? When individuals are younger they are more likely to accept offers from the informal sector. That decreases as they accumulate more resources (Finamor, 2024). Therefore, a relevant source of heterogeneity in youth responses to parental job loss is the age at which the shock occurs. Youth at different stages of the school-to-work transition face distinct outside options, which may shape both their likelihood of entering the labor market and the type of job they accept.

Table 5 in the Appendix presents employment effects by age group and sector. For those aged 14–20, the probability of being employed increases by 3.4 percentage points, with 58.9% of those employed working in informal jobs without a formal contract, compared to only 29.4% in formal employment. In contrast, for individuals aged 21–24, the probability of employment rises

more significantly (9.1 percentage points), and the distribution between formal and informal jobs is more even: 51.6% are employed formally. These results reinforce the idea that the timing of exposure to an economic shock shapes labor market trajectories. If a financial shock forces younger individuals into the labor market, they are more likely to accept low-quality jobs, potentially limiting future opportunities. Meanwhile, older youth who experience the same shock have a higher probability of securing a formal job, reducing the likelihood of being trapped in precarious employment.

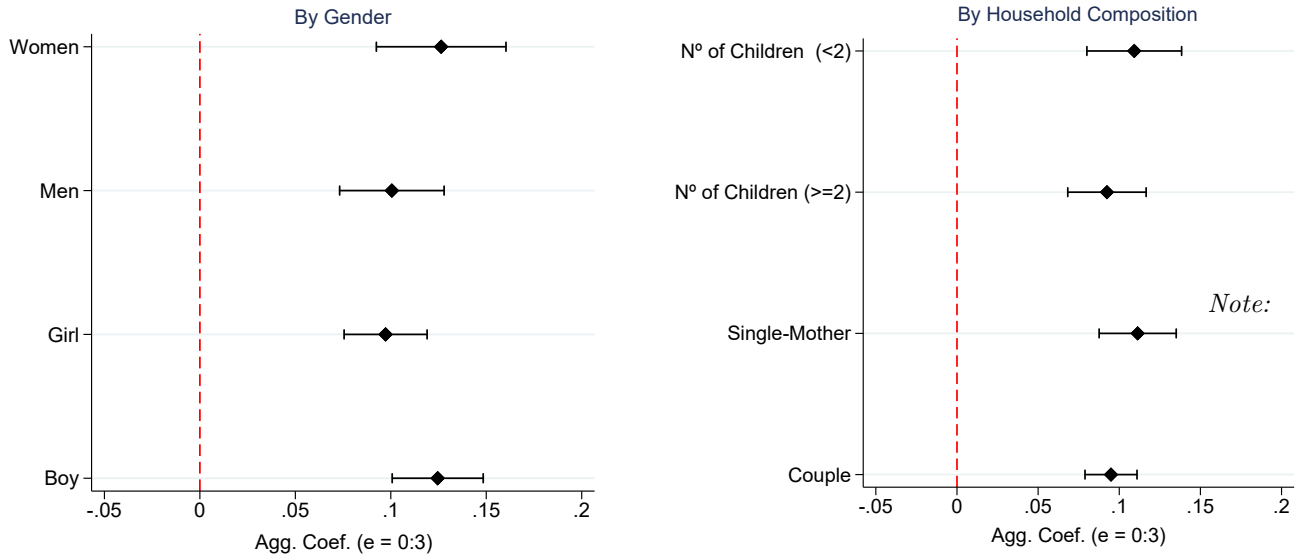
Table 7 in the Appendix reports the full event-study estimates by age group.

9 Heterogeneity Analysis

In this section, I investigate how exposure to parental job loss affects children based on baseline family characteristics, focusing on gender, single-parent status, household size, and maternal education. Figure 6 shows that the effects of parental job loss on youth do not significantly vary by household composition or the gender of the household head. Although boys show a higher increase in labor supply than girls, the difference is not statistically significant. The absence of significant gender differences is noteworthy, as one might expect boys to be more responsive to household income shocks given traditional gender roles in Brazil. However, the data suggest that both boys and girls adjust their labor supply in similar ways when faced with parental displacement, perhaps reflecting the severity of the income shock and the limited alternatives available to both genders in the informal labor market.

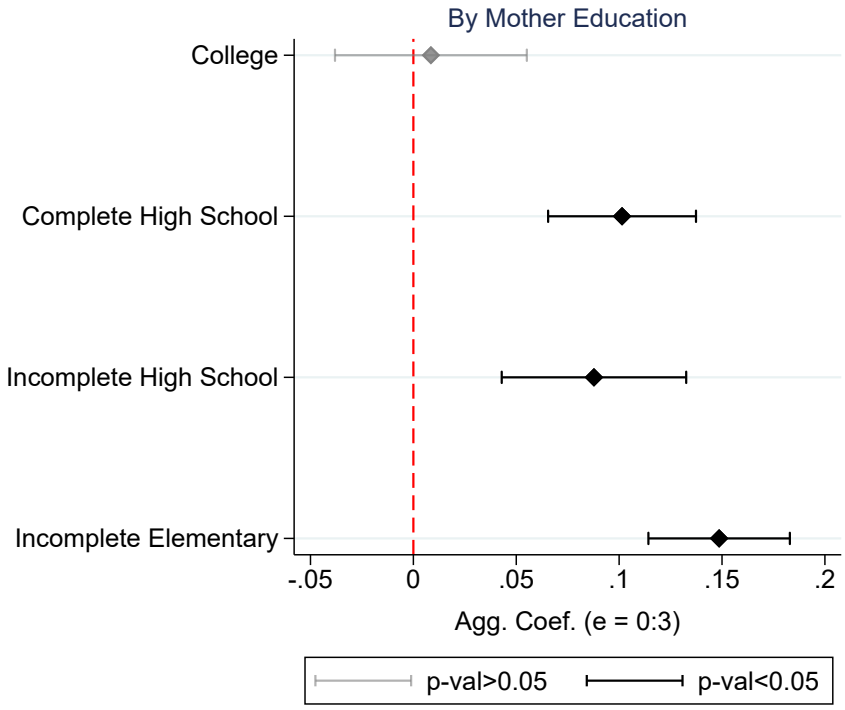
By contrast, the effects vary considerably with the level of parental education and age. Figure 7 presents the results when we split the sample by the education level of the mother, ranging from incomplete elementary school to college education. The results indicate that the effect of parental job loss is significant and large for youth whose household head has not completed elementary school, while no effect is observed for those with more highly educated parents. This result is in line with previous studies showing that mother schooling is positively associated with better outcomes for children (Duflo et al., 2024). The gradient by maternal education is consistent with the mechanisms outlined above: families with lower parental education are more likely to face binding financial constraints and have fewer resources to buffer against income shocks, making their children more responsive to parental displacement.

Figure 6: Heterogeneous Effects by Family Characteristics



This figure plots aggregated treatment effects and 95% confidence intervals for the impact of parental job loss on youth labor force participation, across subgroups defined by individual and household characteristics. Estimates are based on a DiD framework using individual-level clustered standard errors. Panel A shows heterogeneity by gender; Panel B by household composition, including the number of children in the household and whether the household is headed by a single mother or a couple. Each point represents the average post-treatment effect on labor force participation for the corresponding subgroup.

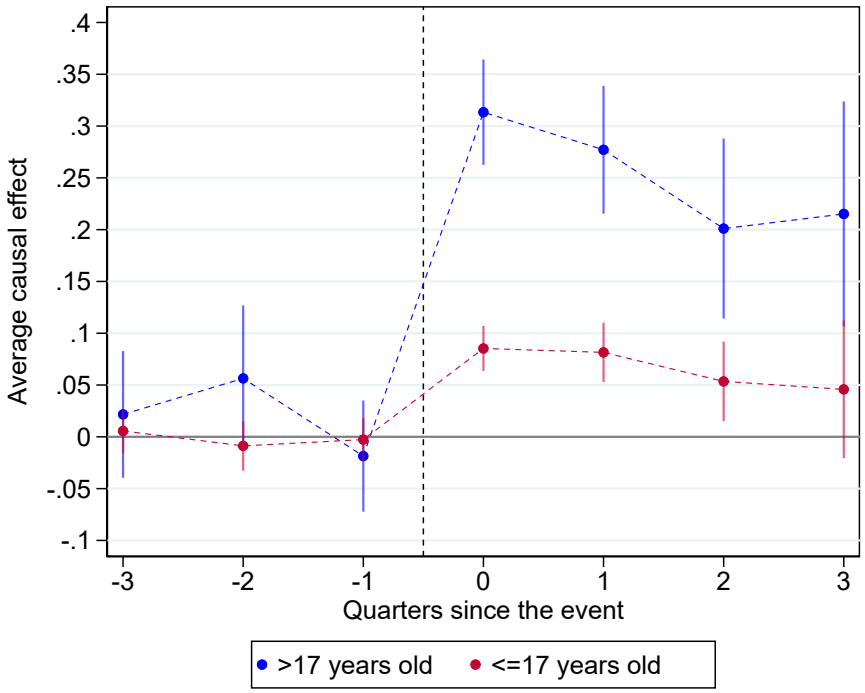
Figure 7: Heterogeneous Effects by Maternal Education



Note: This figure plots aggregated treatment effects and 95% confidence intervals by maternal education level, ranging from incomplete elementary school to college education. Each point represents the average post-treatment effect on labor force participation for the corresponding subgroup.

Figure 8 shows how the effect of parental job loss on youth labor supply varies significantly by age group. Older youth (18–24) exhibit a sharper and more persistent increase in labor force participation, with a peak effect of 26.5% relative to their baseline, while the effect for younger youth (14–17) reaches 35.7%. The larger participation rate among older youth implies that the increase translates to more sustained labor market engagement. This pattern is consistent with the notion that older youth, being closer to the school-to-work transition, are more readily available to respond to household income shocks, while younger adolescents face more constraints—such as schooling obligations and legal restrictions on employment. The differential response by age group has important implications for understanding how the same household shock can set youth on different economic trajectories depending on when it occurs during their formative years.

Figure 8: Effect of Parental Job Loss on Youth Labor Supply, by Age



Note: Dynamic treatment effects by age group, estimated using Equation 2, with 95% confidence intervals.

10 College Attendance

Parental job loss may affect youth outcomes beyond the labor market. In this section, I examine its impact on college attendance. Brazil presents an especially relevant institutional setting for this analysis. The higher education system combines a tuition-free public sector—more closely aligned with the European model—with a large private sector, where enrollment can be supported by student loan programs, resembling aspects of the U.S. system. This dual structure provides a useful context to examine whether the impact of parental job loss on college attendance varies across institution types. Furthermore, although a small share of youth enter higher education, dropout rates exceed 50% (Gomes and Hirata, 2022). Therefore, these findings can provide important insights into understanding factors that undermine young people's retention in higher education. To the best of my knowledge, no prior study has assessed how parental job displacement influences higher education in a developing country.

To analyze this relationship, I focus on individuals aged 18 to 24 who, in their first interview, report being enrolled in higher education. The classification between public and private institutions is available from 2017 onward.

Figure 9: Effect of Parental Job Loss on College Attendance

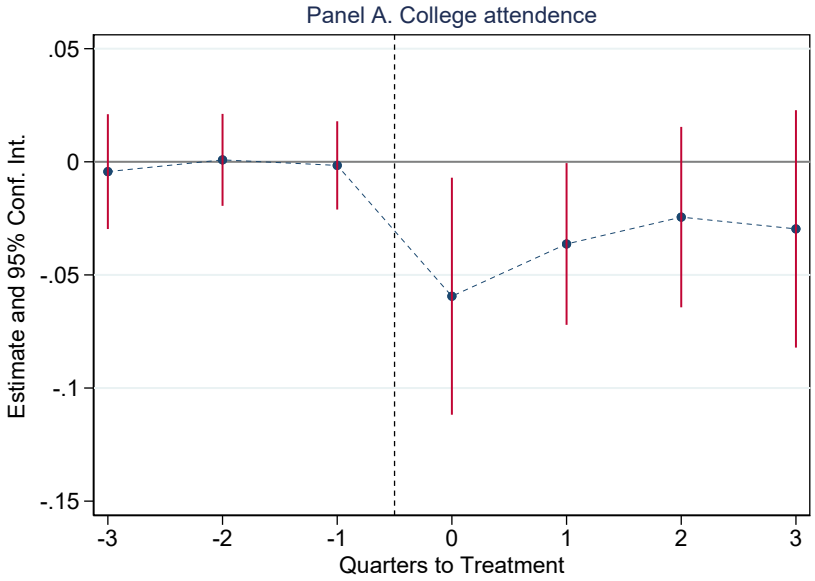
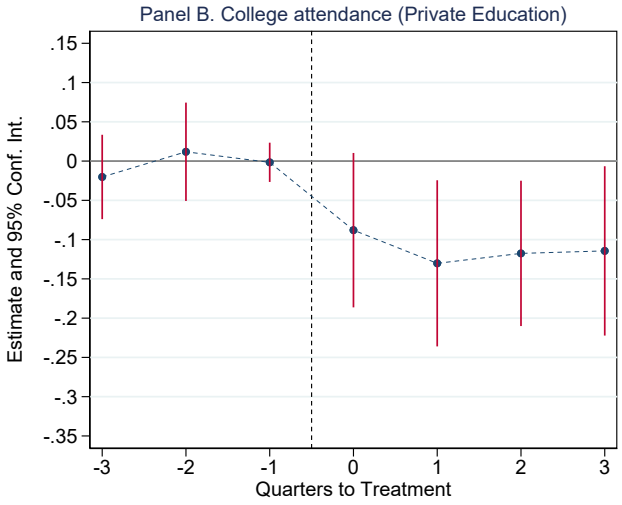
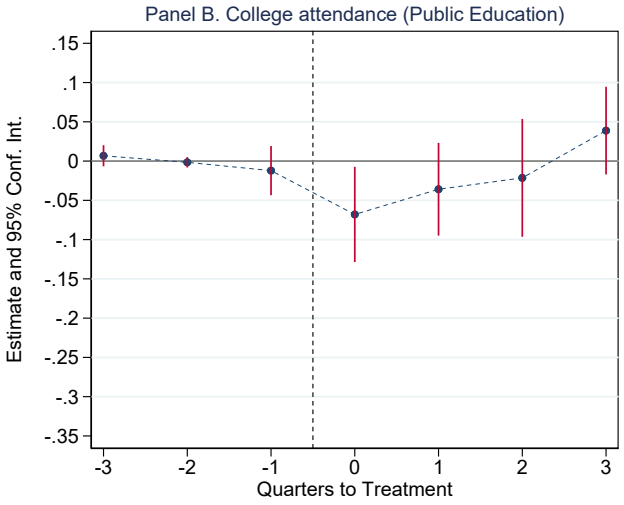


Figure 10: Effect of Parental Job Loss on College Attendance, by Institution Type



Panel A: Private



Panel B: Public

Figure 9 shows the overall impact of parental job loss on college attendance among youth aged 18 to 24. In the quarters following the shock, there is a decline in college attendance of approximately 5 percentage points relative to the baseline level observed before the displacement. The effect becomes less pronounced from the second quarter onward.

Figure 10 disaggregates the results by type of institution. Panel A displays the effects for

students enrolled in private education. Following parental job loss, college attendance in private institutions falls by around 10 percentage points in the last post-treatment period. Despite the wide confidence intervals, the decline is persistent and statistically significant in the first and third quarters after the shock. Panel B presents the effects for students in public institutions. There is a reduction in attendance in the immediate quarter following parental job loss, but the estimates remain close to zero and are not statistically different from zero after the first quarter.

One possible explanation for the observed heterogeneity relates to the structure of the Brazilian higher education system. Public universities offer tuition-free education and student support programs, which can alleviate students from short-term income shocks and facilitate their eventual return to school. The initial decline in attendance could reflect a temporary withdrawal from studies to help support household income, followed by re-enrollment as conditions stabilize. In contrast, in the private sector—where students are responsible for tuition payments—parental income loss may directly compromise educational continuity, resulting in more persistent dropouts.

Nonetheless, it is not possible to rule out alternative mechanisms, including selection. Despite the expansion of affirmative action policies over the past decade, inequality in access to public universities remains substantial.[37] It is therefore possible that students attending public institutions differ systematically in both observable and unobservable characteristics, including financial resilience, which could make them more likely to return to their studies after a financial shock. Sample size limits the precision of my estimates and prevents a more detailed exploration of mechanisms. Future research could leverage administrative data to better identify these channels and assess whether student loan and social assistance programs mitigate the impact of household shocks on college education.

The evidence presented here contributes to a still limited understanding of how parental job loss affects college enrollment in countries with restricted access to credit, as is the case in much of the developing economies. Hilger (2016) finds no significant effect of parental job loss on college enrollment among low-income students in the U.S., attributing this to the availability of generous financial aid programs such as the Pell Grant.[38] My findings suggest that the effects of parental job loss on college attendance observed in high-income contexts may not extend to settings with weaker credit markets. This contrast highlights how the presence or absence of financial aid

[37] Ferreyra et al. (2017) and Ristoff (2014) show that between 2004 and 2015, the share of low-income students in public universities remained stable at around 24%, while increased demand among the bottom four income quintiles was absorbed primarily by the private sector. Mello (2022) argues that the simultaneous implementation of a centralized admissions system and quota policies may have limited the effectiveness of these measures in broadening access.

[38] Fradkin et al. (2019) do not analyze college enrollment, as university tuition in Belgium is heavily subsidized, reducing the financial impact of parental job loss. They reference Hilger (2016) as an upper bound.

programs mediates the transmission of labor market shocks to educational outcomes.

11 Mechanisms

Although the evidence points to tightening financial constraints as a potential driver of the observed patterns in youth behavior following parental job loss, we cannot rule out other possible explanations.

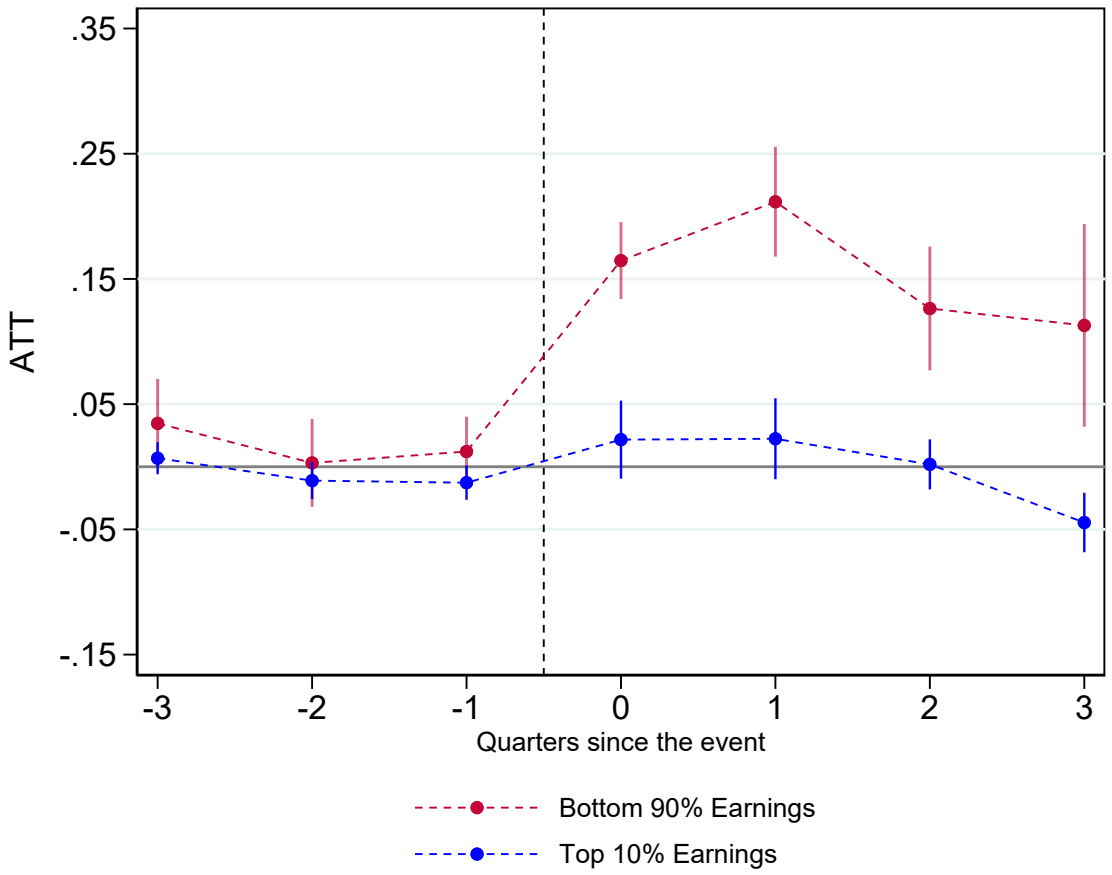
Parental job loss can generate stress within the household and negatively affect the mental health of parents (Zimmer, 2021) and their children (Fontes et al., 2024). If unemployed parents spend their time at home, their children may wish to find a job faster as a means of gaining autonomy. This type of response is not necessarily financial in nature and may be particularly relevant for the age group studied, as young people are more likely to engage in risky behavior without considering the consequences (Spear, 2000). Adolescence is not only a period of economic dependence, but also one of behavioral vulnerability. Evidence from neuroscience shows that the adolescent brain is still undergoing structural maturation, with heightened sensitivity to immediate rewards and limited consideration of long-term consequences. These features help explain why short-run financial shocks—such as parental job loss—can trigger disproportionate behavioral responses, particularly in settings where alternative buffers are scarce.

On the other hand, prior research has documented a strong correlation between youth decisions regarding work and education and household income. In particular, income gains among parents have been shown to have a positive correlation that young people (15–24) will remain in school and reduce their participation in the labor market (Cabanas et al., 2014).

To better understand the mechanism driving the results, I proxy household income using the sum of parental labor earnings reported in the first interview, and divide the sample into the top 10% and bottom 90% of the distribution. The results in Figure 11 show that the aggregate effect for families in the top decile is statistically insignificant, while for the bottom 90% it reaches approximately 20% in the quarter following the shock. Household income likely reflects the family's ability to save or access credit. In practice, low-income households may lack these financial buffers, which lowers the utility of remaining unemployed for youth. As a result, they increase job search efforts and are more likely to accept available opportunities (mostly in the informal sector) quickly. This is precisely what we observe in the baseline estimates.

This pattern is consistent with a liquidity channel. Low-income households lack savings, face constrained credit markets (Corado et al., 2024), and have limited access to formal insurance. When a parent loses a job, the opportunity cost of remaining out of the labor force

Figure 11: Average Effect of Parental Job Loss on Youth Labor Supply, by Household Income



Note: This figure shows the average effect of parental job loss on youth labor force participation, separately for families in the top 10% and bottom 90% of household labor income, measured at baseline (first interview).

increases sharply for youth in these households, pushing them to accept available opportunities—predominantly in the informal sector. While I do not directly test whether reservation wages fall, the shift toward informality suggests that financial pressure may also reduce youths' ability to wait for better job matches. Informality among 14–24-year-olds is widespread, with about 55% of employed youth working in unregistered jobs during the period. Following the shock, however, over 70% of newly employed youth enter informal employment, with little evidence of transitions into self-employment. One plausible explanation is that, when liquidity constraints bind, the opportunity cost of continued search increases, making low-barrier jobs in the informal sector more acceptable in the short run.

The decline in college attendance (Section 10), particularly when disaggregated by institution type, provides a second piece of evidence that helps discriminate between mechanisms. The drop in attendance is concentrated among students enrolled in private institutions, where tuition

payments are directly tied to household resources. In contrast, students attending tuition-free public universities experience only a short-lived decline, with attendance recovering within one quarter. This asymmetry is difficult to reconcile with a pure stress or role-model mechanism: if the behavioral response were driven primarily by parental stress, household conflict, or changes in the perceived value of education, one would expect similar declines in both public and private institutions. The fact that the effect is concentrated where tuition costs create a direct link between household income and educational continuity points to a financial channel.

Taken together, two patterns in the data jointly point to household liquidity as the dominant mechanism. First, the income split: effects are large and significant for the bottom 90% of the income distribution but statistically indistinguishable from zero for the top 10%. If stress, role-model effects, or household conflict were the primary drivers, they should operate similarly across the income distribution—parental job loss is stressful regardless of household wealth. The fact that only financially constrained households exhibit behavioral responses is consistent with a binding liquidity constraint. Second, the college split: the decline in attendance is concentrated in private institutions where tuition must be paid, while enrollment in tuition-free public universities recovers quickly. A stress mechanism would not generate this asymmetry; a liquidity mechanism would.

While I cannot completely rule out that alternative channels play some role, the combination of these two results—concentration among low-income households *and* concentration in tuition-dependent institutions—is most parsimoniously explained by a unified financial mechanism: when household income drops and credit markets cannot absorb the shock (Corado et al., 2024), youth reallocate from human capital investment toward immediate income generation through the informal sector.

12 Robustness

The main results are robust to a series of specification checks. Robustness exercises include reweighting by propensity scores using the doubly robust estimator proposed by Callaway and Sant'Anna (2021), incorporating a rich set of covariates (race, gender, state of residence, mother's educational attainment, age, year, number of children aged 14–24). The identification strategy thus relies on the parallel trends assumption, conditional on these covariates. I also relax the requirement that the partner remains employed at the time of the job loss. Across all specifications, the main results remain consistent in both sign and magnitude.

I employ three alternative approaches (Figures 16–18 in the Appendix). First, I use the

doubly robust estimator proposed by Callaway and Sant'Anna (2021), which reweights observations using propensity scores estimated from the rich set of covariates listed above. The main estimates remain stable (Figure 16). Second, I relax the requirement that the spouse remains employed at the time of the job loss, allowing for the possibility that both parents experience simultaneous labor market disruptions. The results are qualitatively unchanged (Figure 17). Third, I estimate the model using only the not-yet-treated as the control group, excluding the never-treated—a more conservative approach that restricts comparisons to households that eventually experience job loss but differ only in timing. Estimates remain consistent in both sign and magnitude (Figure 18).

13 Discussion

In a country where most youth work in the informal sector and more than half of college entrants drop out before completing their degree, a sudden income shock—such as parental job loss—can have substantial effects on young people's transitions into the labor market and higher education. I investigated this hypothesis using nationally representative household survey data from Brazil (PNADC), which captures both formal and informal employment. I applied a difference-in-differences framework that exploits variation in the timing of parental job displacement to estimate causal effects.

I find that parental job loss increases youth labor force participation, mainly through informal jobs. Younger individuals are more likely to enter informal jobs without contracts, while older youth are more likely to access formal work. These patterns are consistent with the idea that informal jobs act as a short-term buffer in the face of tightening liquidity constraints. I also examine college attendance and find a decline following parental job loss, especially among students in private institutions—where tuition is directly tied to household income. For students in public universities, enrollment temporarily declines but recovers after one quarter.

To investigate mechanisms, I document a large and sustained drop in parental earnings one year after separation. The adjustment is concentrated among youth from pre-shock low-income households, especially those in the bottom decile of pre-shock income. These findings suggest that financial distress is a key driver.

Overall, this paper contributes to the literature on disadvantaged youth by providing empirical evidence on how negative household income shocks affect their behavior in the labor market and higher education. The evidence presented here raises an important question for future research: whether the short-run labor supply responses documented in this paper—particularly the

entry into informal employment and exit from education—generate persistent effects on youth's long-term economic trajectories. While the data limitations of the PNADC panel prevent direct assessment of long-run outcomes, the existing literature on the scarring effects of early informality (Cruces et al., 2012) and the persistent consequences of adverse labor market entry conditions (Wachter, 2020) suggests that these short-run adjustments may carry substantial long-term costs. Future work can further explore whether these short-run adjustments persist, and how they influence long-term outcomes.

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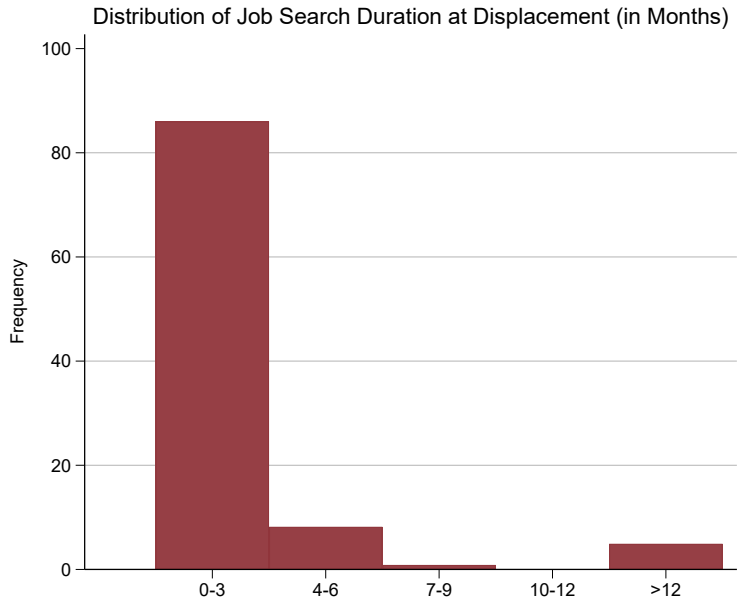


Figure 12: Distribution of Job Search Duration at Displacement
Note: This figure displays the distribution of job search duration (in months) at the time of displacement.

A Appendix

A.1 Data

Table 2: Summary of Sample Restrictions

Step	Obs.	LFP (%)	Employed (%)	Female (%)	School (%)
(1) All children 14–24	2,185,103	36.2	27.1	48.5	68.7
(2) Living with parents	1,700,368	34.9	26.0	46.2	73.3
(3) Parents aged 25–59	1,614,444	34.8	25.8	46.2	73.8
(4) Valid individual identifier	1,492,794	35.0	26.1	46.4	74.1
(5) Two or more interviews	1,382,628	34.9	26.1	46.4	74.4

A.2 Attrition

Table 3: PNADC Rotating Panel Design

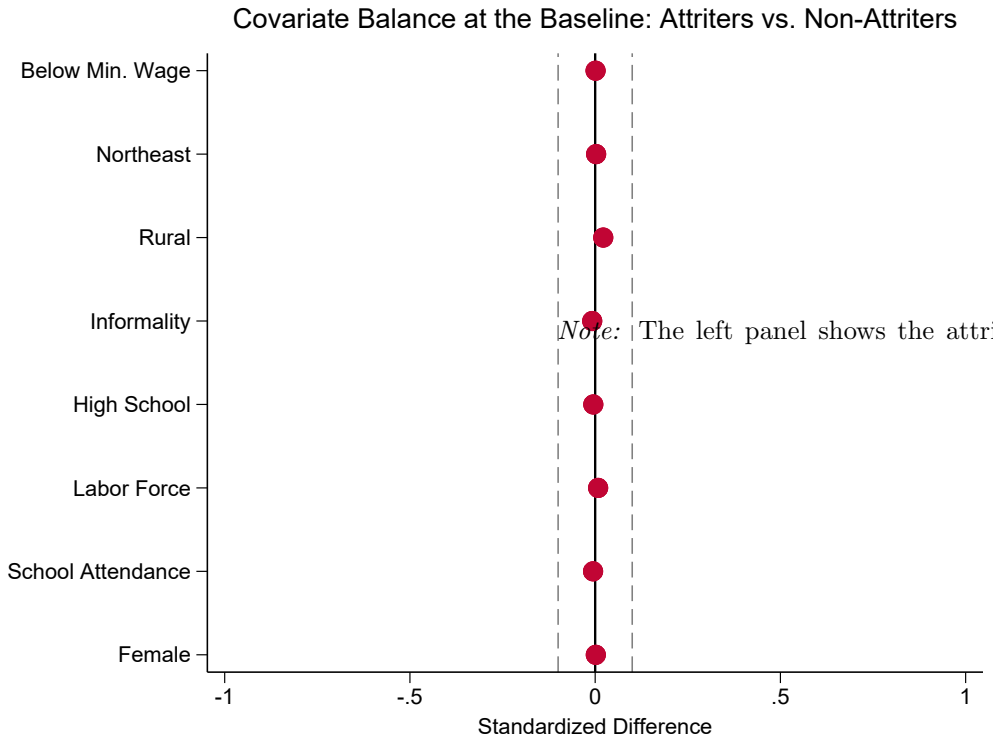
Quarter	Year	Rotating groups											
		A	B	C	D	E	F	G	H	I	J	K	L
1	2016	5	4	3	2	1							
2	2016		5	4	3	2	1						
3	2016			5	4	3	2	1					
4	2016				5	4	3	2	1				
1	2017					5	4	3	2	1			
2	2017						5	4	3	2	1		
3	2017							5	4	3	2	1	
4	2017								5	4	3	2	1

Table 4: Baseline Characteristics: Attriters vs. Non-Attriters

	(1) Attriters	(2) Non-Attriters
Labor Force	0.608	0.600
	(0.001)	(0.001)
High School Completion	0.230	0.237
	(0.002)	(0.002)
Female	0.516	0.514
	(0.001)	(0.001)
School Attendance	0.308	0.314
	(0.001)	(0.001)
Informal	0.482	0.490
	(0.002)	(0.002)
Below Minimum Wage	0.267	0.276
	(0.002)	(0.002)
Rural	0.280	0.266
	(0.001)	(0.001)
Northeast	0.343	0.340
	(0.001)	(0.001)
Observations	241,139	625,600
Share (%)	18%	82%

Notes: Mean values of baseline covariates (first interview) for individuals who attrited (did not appear in the last interview) and those who remained in the sample. The main sample consists of families with children aged 14 to 24 and household heads or spouses aged 25 to 59; only individuals appearing at least twice are included. Standard errors in parentheses.

Figure 13: Attrition and Covariate Balance



Note: The left panel shows the attrition rate across interviews. The right panel presents standardized mean differences for key baseline covariates between attriters and non-attriters. Dashed vertical lines at -0.2 and 0.2 indicate conventional balance thresholds (Imbens and Rubin, 2015).

A.3 Variable Definitions

Variable	Definition
Unemployed	Not engaged in any work, available to begin work, and actively seeking employment during the reference period.
Household Head	The individual identified by household members as the primary person responsible for the household.
Job Search	Deliberate actions aimed at obtaining employment, including contacting employers, registering for exams, consulting agencies, responding to advertisements, networking, or initiating self-employment activities.
Employed	Individuals who worked at least one hour in paid employment or in unpaid work contributing to a household member's economic activity, including those temporarily absent.
Labor Force	Employed plus unemployed individuals.
LF Participation Rate	Share of individuals in the labor force relative to total working-age population.
Non-Response Weight	Adjustment weight constructed by IBGE to account for nonresponse (refusals, inability to contact, etc.).

A.4 The PNADC Survey

The Continuous National Household Sample Survey (PNADC) is conducted by the Brazilian Institute of Geography and Statistics (IBGE), a federal agency under the Ministry of Planning and Budget. The PNADC is publicly available and constitutes the primary source for labor market statistics in Brazil. According to Donovan et al. (2023), who compare household surveys across 48 countries, the PNADC ranks as the second-largest quarterly household survey globally in terms of sample size and stands out for its detailed variable coverage.

The survey adopts a rotating panel scheme in which each sampled household is interviewed for five consecutive quarters. In each quarter, approximately 211,000 households are interviewed, covering roughly 16,000 census sectors across 3,500 municipalities. The rotation scheme ensures that in any given quarter, one-fifth of the sample is being interviewed for the first time and one-fifth is completing their fifth and final interview. This structure allows for both cross-sectional and longitudinal analyses, although the longitudinal dimension requires the construction of individual identifiers, as IBGE provides only household-level identifiers.

The survey collects detailed information on demographic characteristics (age, gender, race, education, household composition), labor market outcomes (employment status, occupation, sector, hours worked, earnings, job search behavior), and education (enrollment, institution type, degree level). For the purposes of this study, the key advantage of the PNADC over administrative data (such as RAIS) is its coverage of the informal sector: all employment—formal, informal, self-employment—is recorded, making it possible to study the full spectrum of youth labor market responses.

The PNADC data used in this study spans the period from the first quarter of 2012 to the fourth quarter of 2019. This period was chosen to exclude the COVID-19 pandemic, which introduced confounding labor market disruptions beginning in 2020. The quarterly data files are downloaded directly from the IBGE website and processed using standardized variable dictionaries provided by the institute.

A.5 Panel Construction and Identification Algorithm

Although the PNADC has a panel structure by design, IBGE does not provide individual-level identifiers for longitudinal tracking. Each household is assigned a unique identifier based on the primary sampling unit (UPA), the household number within the UPA, and the rotation group. Within a household, individuals are identified by their position in the household roster. However, changes in household composition, reporting errors, and non-response across waves

mean that simply matching individuals by roster position is insufficient.

To construct an individual-level panel, I employ the identification algorithm developed by Ribas and Soares (2008) and subsequently refined by Osorio (2022). The algorithm proceeds in two stages:

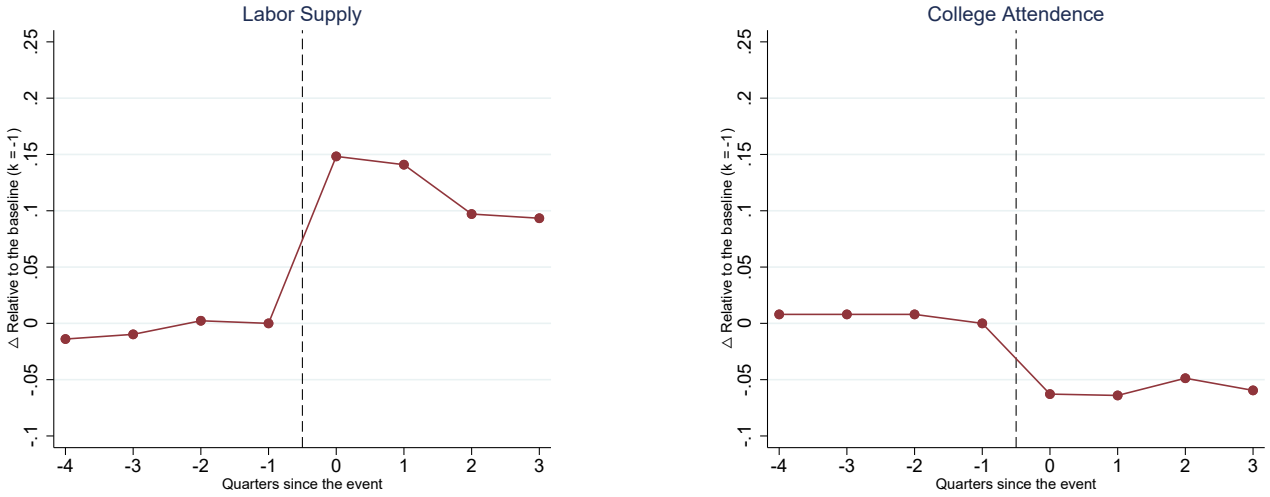
Basic identification. Individuals are matched across survey waves using fixed characteristics: date of birth (year and month), gender, and position in the household. A match is established when all characteristics are identical across two adjacent interviews within the same household.

Advanced identification. Individuals who remain unmatched after the basic stage enter a second round of identification that allows for small discrepancies in reported characteristics. This stage is particularly important given that survey respondents may report slightly different birth dates or household positions across interviews. The advanced algorithm tolerates small inaccuracies while maintaining high match quality, thereby reducing panel attrition.

The identification algorithm processes the data household by household within each rotation group, comparing individual records across all five potential interview waves. The output is a unique individual identifier that allows tracking the same person over time.

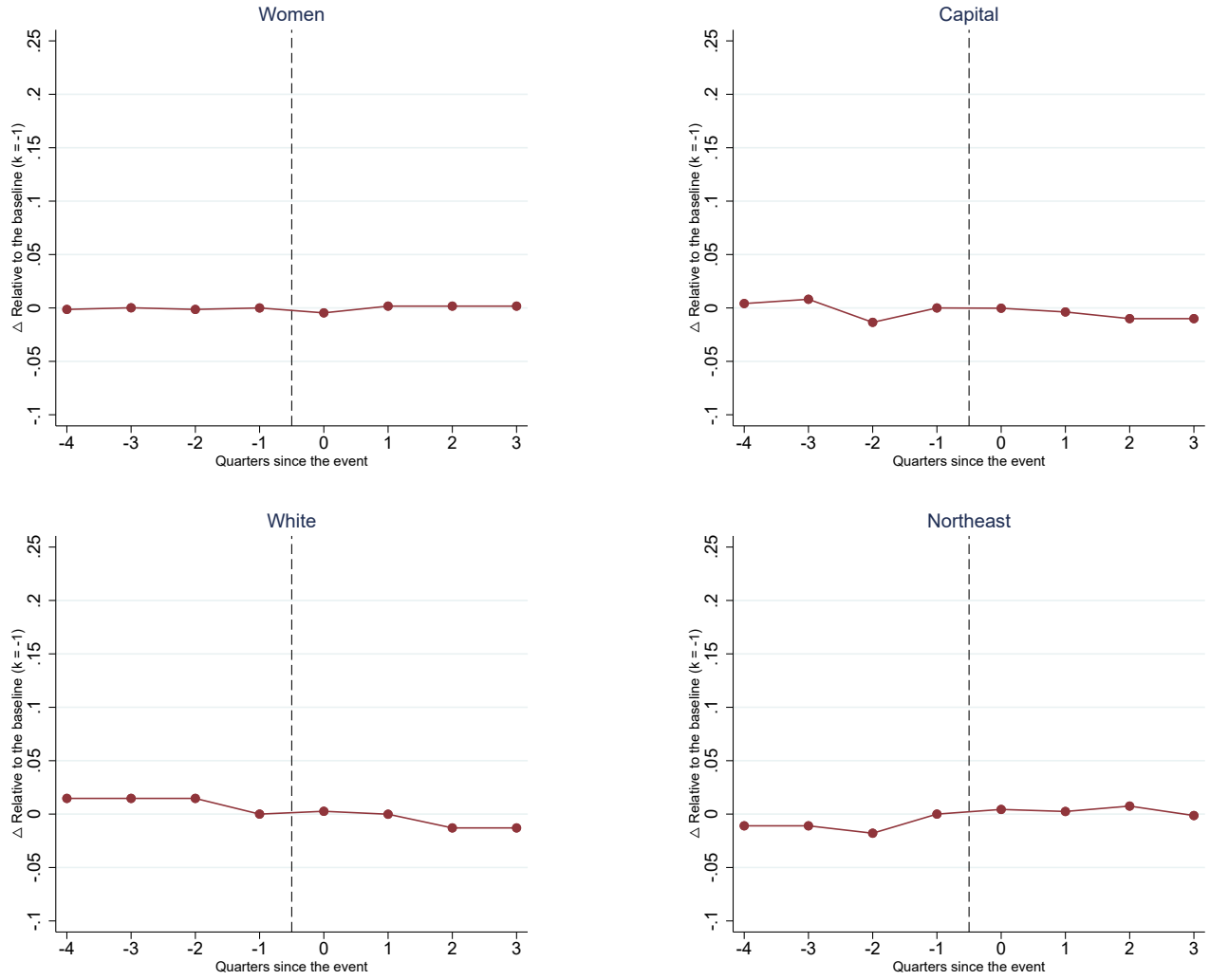
A.6 Descriptive Evidence

Figure 14: Main Outcomes: Trends Before and After Parental Job Loss



Note: This figure plots the average probability of being in the labor force (left panel) and attending higher education (right panel) relative to the quarter of parental job loss ($t = 0$, vertical dashed line). The horizontal axis shows time in quarters relative to the event, and the vertical axis shows the deviation from the baseline quarter ($t = -1$).

Figure 15: Covariate Balance: Trends Before and After Treatment



Note: This figure shows pre- and post-treatment trends in key covariates for the treatment and control groups. The covariates include demographic characteristics (gender, education, rural residence), labor market indicators (informality, labor force participation), and regional identifiers.

A.7 Results

Table 5: Employment Effects by Age Group and Sector

Sector	Employment Type	14–20	P(y | Emp.)	21–24	P(y | Emp.)
	Any Work	0.034***	100%	0.091***	100%
		(0.005)		(0.027)	
Formal	Registered	0.010***	29.4%	0.047**	51.6%
		(0.003)		(0.018)	
Informal	Self-Employed	0.004	11.8%	0.014	15.4%
		(0.002)		(0.008)	
	Unregistered	0.020***	58.9%	0.030	33.0%
		(0.004)		(0.019)	

Note: This table reports employment effects of parental job loss by age group and sector. P(y | Emp.) is the share of the employment effect attributable to each type. Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 6: Event-Study Estimates: Main Results

	Job Search	*Employment*		
	Labor Supply	Employed	Earnings	Hours
Agg. Coef ($e = -3$)	0.007	-0.003	-4.832	-0.142
	(0.011)	(0.006)	(4.950)	(0.241)
Agg. Coef ($e = -2$)	0.005	-0.001	11.516	0.202
	(0.012)	(0.007)	(11.980)	(0.302)
Agg. Coef ($e = -1$)	-0.008	-0.005	-14.064	-0.380
	(0.010)	(0.005)	(9.825)	(0.241)
Agg. Coef ($e = 0$)	0.133***	0.043***	44.272***	1.675***
	(0.011)	(0.007)	(8.289)	(0.275)
Agg. Coef ($e = 1$)	0.121***	0.055***	47.516***	1.811***
	(0.014)	(0.010)	(10.359)	(0.360)
Agg. Coef ($e = 2$)	0.074***	0.033**	28.268**	0.864**
	(0.018)	(0.013)	(12.586)	(0.436)
Agg. Coef ($e = 3$)	0.076**	0.059**	43.454**	1.709*
	(0.030)	(0.025)	(21.988)	(0.883)
Agg. Coef ($e = 0{:}3$)	0.101***	0.048***	40.877***	1.515***
	(0.013)	(0.010)	(9.213)	(0.346)
Mean Dep. Var. ($e = -1$)	0.422	0.276	278.812	9.823
Magnitude ($e = 0{:}3$)	23.9%	17.3%	14.7%	15.4%
# Treated	21,689	21,689	21,689	21,689
# Control	568,719	568,719	568,719	568,719

Note: This table reports event-study estimates of the effect of parental job loss on youth labor market outcomes. Each column corresponds to a different outcome. Estimates are obtained using the Callaway and Sant'Anna (2021) estimator. Standard errors, clustered at the individual level, are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

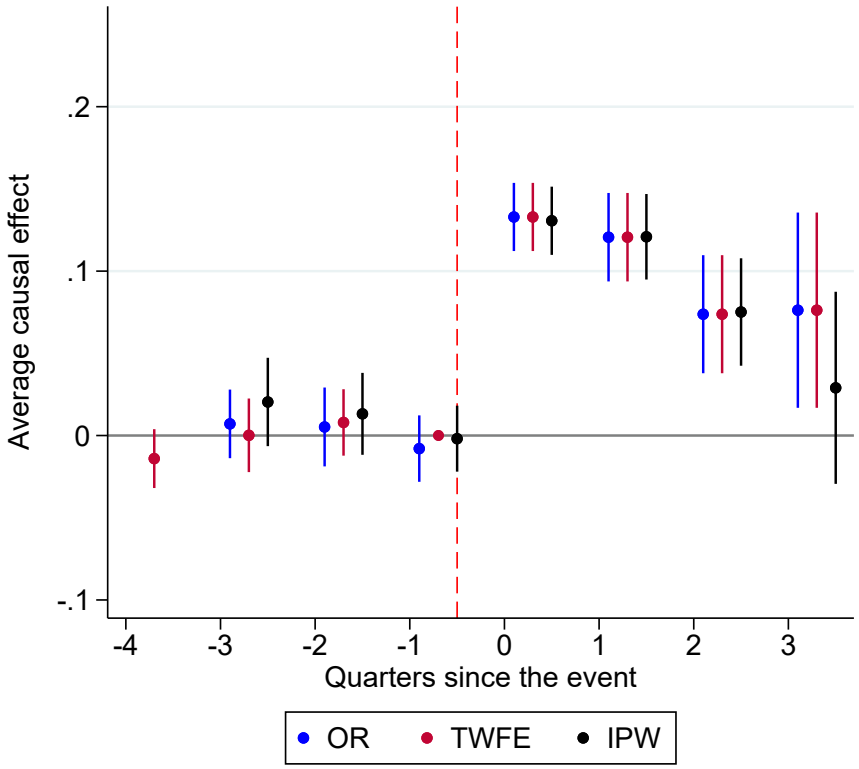
Table 7: Heterogeneity by Age Group

	Young Adult (18–24)	Adolescent (14–17)
Agg. Coef ($e = -3$)	0.022	0.006
	(0.031)	(0.011)
Agg. Coef ($e = -2$)	0.056	-0.009
	(0.036)	(0.012)
Agg. Coef ($e = -1$)	-0.019	-0.003
	(0.027)	(0.011)
Agg. Coef ($e = 0$)	0.313***	0.085***
	(0.026)	(0.011)
Agg. Coef ($e = 1$)	0.277***	0.082***
	(0.032)	(0.015)
Agg. Coef ($e = 2$)	0.201***	0.054**
	(0.044)	(0.020)
Agg. Coef ($e = 3$)	0.215***	0.046
	(0.055)	(0.034)
Post Treatment ($e = 0{:}3$)	0.252***	0.067***
	(0.028)	(0.014)
Mean Dep. Var. ($e = -1$)	0.704	0.261
Magnitude ($e = 0{:}3$)	35.7%	25.5%
# Treated	13,212	8,477
# Control	314,644	254,075

Note: This table reports event-study estimates of the effect of parental job loss on youth labor force participation, separately by age group. Estimates are obtained using the Callaway and Sant'Anna (2021) estimator. Standard errors, clustered at the individual level, are in parentheses. Significance levels: *** p<0.01, ** p<0.05, * p<0.1.

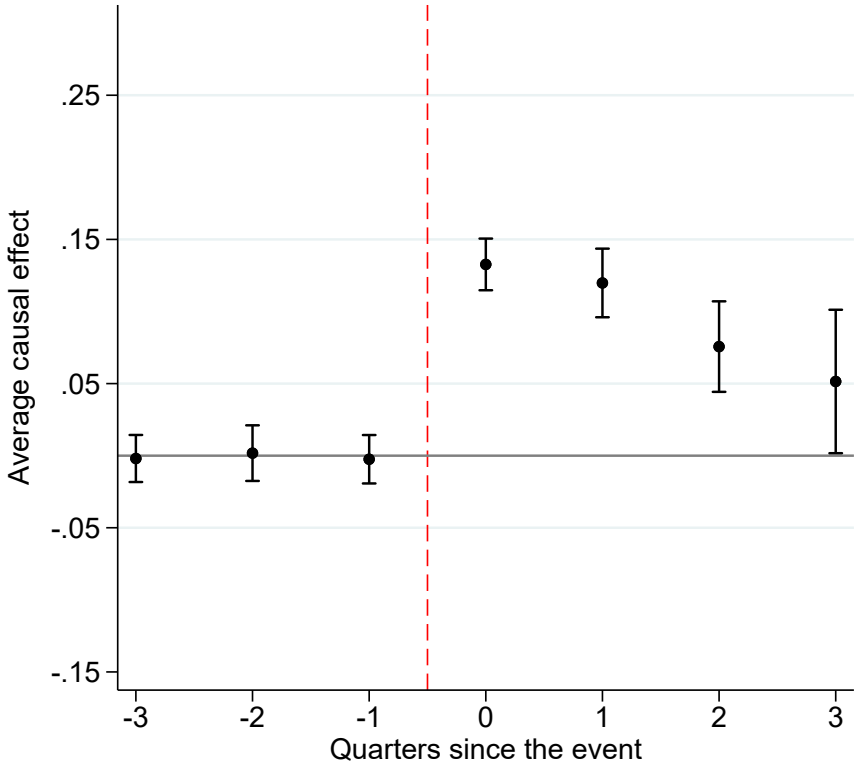
A.8 Robustness

Figure 16: Robustness: Alternative DiD Estimators



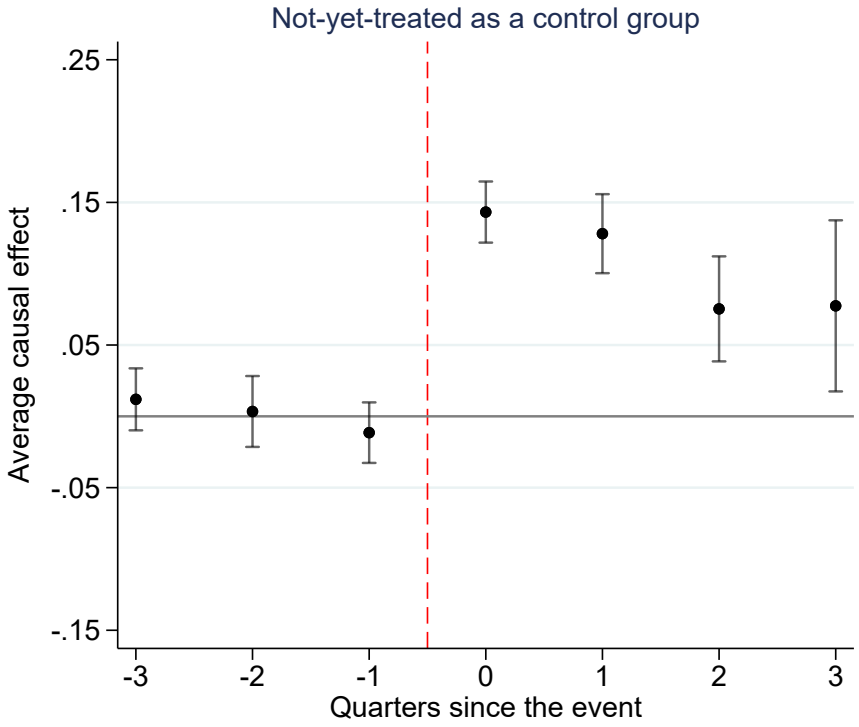
Note: This figure presents dynamic treatment effects on youth labor force participation using the doubly robust estimator of Callaway and Sant'Anna (2021), with 95% confidence intervals. The specification reweights observations using propensity scores based on a rich set of covariates.

Figure 17: Robustness: Relaxing Spouse Employment Restriction



Note: This figure presents dynamic treatment effects on youth labor force participation when the requirement that the spouse remains employed is relaxed, with 95% confidence intervals.

Figure 18: Robustness: Not-Yet-Treated Control Group Only



Note: This figure presents dynamic treatment effects on youth labor force participation using only the not-yet-treated as the control group, with 95% confidence intervals.