Pontifícia Universidade Católica
do Rio de Janeiro

Isabella Helter Claudino

Youth Responses to Parental Unemployment in a Context of High Informality: Evidence from Brazil

Dissertação de Mestrado

Masters dissertation presented to the Programa de Pós–graduação em Economia, do Departamento de Economia da PUC-Rio in partial fulfillment of the requirements for the degree of Mestre em Economia.

Advisor : Prof. Gustavo Gonzaga
Co-advisor: Prof. Juliano Assunção

Rio de Janeiro
April 2025

Pontifícia Universidade Católica
do Rio de Janeiro

Isabella Helter Claudino

Youth Responses to Parental Unemployment in a Context of High Informality: Evidence from Brazil

Master's dissertation presented to the Programa de Pós–graduação em Economia da PUC-Rio in partial fulfillment of the requirements for the degree of Mestre em Economia. Approved by the Examination Committee:

Prof. Gustavo Gonzaga
Advisor
Departamento de Economia – PUC-Rio

Prof. Juliano Assunção
Co-advisor
Departamento de Economia – PUC-Rio

Prof. Rudi Rocha
FGV EAESP

Prof. Cecília Machado
PUC Rio

Rio de Janeiro, April 16th, 2025

Isabella Helter Claudino

B.A. in Economics, Universidade Federal Fluminense (UFF), 2022.

Bibliographic data

Helter, Isabella

Youth Responses to Parental Unemployment in a Context of High Informality: Evidence from Brazil / Isabella Helter Claudino; advisor: Gustavo Gonzaga; co-advisor: Juliano Assunção. – 2025.

62 f: il. color. ; 30 cm

Dissertação (mestrado) - Pontifícia Universidade Católica do Rio de Janeiro, Departamento de Economia, 2025.

Inclui bibliografia

1. Economia – Teses. 2. Perda de emprego dos pais. 3. Jovens. 4. Informalidade. I. Gonzaga, Gustavo. II. Assunção, Juliano. III. Pontifícia Universidade Católica do Rio de Janeiro. Departamento de Economia. IV. Título.

CDD: 004

Acknowledgments

I am grateful to my mother and my entire maternal family. Being the first in my family to earn a college degree - and now a master's - is not just my achievement. It is yours. You worked hard your whole lives so I could reach this point. You ran a marathon so I could take the final step. I am proud to come from a family with so much strength and history.

I am thankful to my advisor, Gustavo Gonzaga, for his extraordinary guidance and for always believing in my potential. His support and the opportunities he gave me throughout my time at PUC-Rio made all the difference. I am also grateful to my co-advisor, Juliano Assunção, for his contagious enthusiasm for this topic since day one - it was essential to keeping this dissertation moving forward. I appreciate the insightful comments and valuable suggestions from the committee members, Rudi Rocha and Cecilia Machado.

To my friends from PUC-Rio, I am thankful for every moment of laughter and every pizza night. I wouldn't have come this far without you. All the partnership helped make this journey truly special. I made friends for life. I am also grateful to my roomies friends Alice, Rafa, and my brother Nicolai for their love, patience, and presence - especially after long study days.

I am thankful to Carlos Corseuil for being one of the first to believe in my potential at IPEA. He showed me that professionalism and intellectual generosity can go hand in hand. His feedback was fundamental to my research. Finally, I would like to thank my former team at IPEA, especially Gabriela Padilha, Felipe Russo, and Maira Franca, for always being generous with their time and helpful with data and technical discussions.

This study was financed in part by the Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - Brasil (CAPES) - Finance Code 001.

Abstract

Helter, Isabella; Gonzaga, Gustavo (Advisor); Assunção, Juliano (Co-Advisor). **Youth Responses to Parental Unemployment in a Context of High Informality: Evidence from Brazil**. Rio de Janeiro, 2025. 62p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

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. However, little is known about how young people respond to such negative shocks in high-informality settings. I examine this question using a difference-in-differences approach and a large panel data from Brazil, which captures both formal and informal employment and tracks over half a million youth–parent pairs for one year. 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. 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. These effects are concentrated among low-income households and contribute to a different perspective on the added-worker effect in credit-constrained settings.

Keywords

Parental Job Loss; Young people; Informality.

Resumo

Helter, Isabella; Gonzaga, Gustavo; Assunção, Juliano. **Respostas dos Jovens ao Desemprego Parental em um Contexto de Alta Informalidade: Evidências do Brasil**. Rio de Janeiro, 2025. 62p. Dissertação de Mestrado – Departamento de Economia, Pontifícia Universidade Católica do Rio de Janeiro.

Em um país onde o trabalho informal é a principal alternativa para os jovens e mais da metade dos estudantes que entram na faculdade abandonam o curso antes de se formar, um choque repentino de renda - como a perda de emprego dos pais - pode alterar significativamente o comportamento de busca por trabalho e a frequência no ensino superior. No entanto, sabe-se pouco sobre como os jovens reagem a esse tipo de choque negativo em contextos com alta informalidade. Examino essa questão utilizando uma abordagem de diferenças em diferenças e dados de painel amplos do Brasil, que capturam tanto o emprego formal quanto o informal e acompanham mais de meio milhão de pares de jovens e seus pais durante um ano. A perda de emprego dos pais aumenta a participação dos jovens no mercado de trabalho em 24%, com quase todo esse ajuste ocorrendo por meio de empregos informais e uma parcela menor através do trabalho por conta própria. Esse aumento na atividade laboral persiste um ano após o choque. Ao mesmo tempo, a permanência na faculdade cai cerca de 10%, impulsionada por saídas de instituições privadas, enquanto a matrícula em universidades públicas eventualmente se recupera com o tempo. Esses efeitos se concentram entre famílias de baixa renda e contribuem para uma nova perspectiva sobre o efeito trabalhador adicional em contextos com restrição de crédito.

Palavras-chave

Perda de emprego dos pais; Jovens; Informalidade.

Table of contents

1
Introduction

In Brazil, where almost 60% of youth work in the informal sector and over half of college entrants drop out, 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 - highlighting the importance of understanding how disadvantaged youth respond to economic shocks (Bandiera et al. (2022))[1]. While a growing literature examines the effects of positive income transfers on youth outcomes (Blattman, Fiala and Martinez (2014), Machado, Szerman and Neto (2025)), evidence of large and negative ones remains limited. This issue could be especially relevant in our context, 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.

This dissertation addresses this question by focusing on parental job loss-a common and economically significant disruption to family income-and examining its impact on young individuals' labor market responses and college attendance. Extensive research has illustrated that job loss has severe repercussions on individuals' lives.[2] Evidence from developed countries also shows that parental job loss can generate spillover effects on children, by reducing educational performance and lowering future earnings (Oreopoulos, Page and Stevens (2008), Rege, Telle and Votruba (2011); Hilger (2016)).

While this literature is well documented for high-income countries, much less is known about its effects on disadvantaged youth in contexts of high informality and credit constraints. A central reason for this gap is the challenge of implementing credible causal identification strategies in these contexts.[3]

[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 urgency of studying disadvantaged youth (15-24 years) and their job search behavior.

[2]See Jacobson, LaLonde and Sullivan (1993); Couch and Placzek (2010); Schmieder, Wachter and Heining (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, examing effects on mortallity (Sullivan and Wachter (2009)) and mental health outcomes (Zimmer (2021)). For a review of this fastly growing literature and others outcomes, see Flaaen, Shapiro and Sorkin (2019).

[3]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

Usually, panel data are unavailable or span short time periods, and surveys often rely on small samples. These challenges are especially pronounced when analyzing youth, most of whom are either employed in the informal sector or unemployed—placing them, by definition, largely outside administrative records.

This dissertation fills this gap by providing causal evidence on how parental job loss affects youth labor supply and higher education in Brazil, using data from the Continuous National Household Sample Survey (PNADC).[4] PNADC is the second-largest quarterly household survey globally in terms of sample size and stands out for its detailed variable coverage (Donovan, Lu and Schoellman (2023)).[5] This dataset yields an initial sample of over two million youth matched to their parents over the study period, allowing for heterogeneity analysis and robustness checks to support a credible investigation of the effects of parental job loss on youth labor supply, informality, and college attendance.

The empirical strategy leverages variation in the timing of parental job loss events within a difference-in-differences (DiD) framework. Following recent methodological advances, the analysis employs estimators that are robust to treatment effect heterogeneity across cohorts and time Callaway and Sant'Anna (2021). The identifying assumptions are supported by several validation exercises: pre-trends are flat and statistically insignificant across all main outcomes, and effect magnitudes remain stable when restricting the sample to youth whose parents eventually lose their jobs—thereby solely exploiting variation in the timing of the job loss. This design helps ensure greater comparability between treated and control units in terms of unobservables. In addition, recent findings from the Brazilian labor market showing that there are no differences in results using mass layoff or layoff provide further credibility to the identifying assumptions.

I define job displacement as the transition from private sector employment to unemployment in the following quarter, for parents aged 25 to 59, excluding individuals who had initiated job search more than one quarter prior to the transition. This narrow definition aims to capture involuntary and unanticipated separations, reducing the likelihood of including voluntary

(2023) leverages the timing of grandmothers' deaths in Mexico as an shock to childcare availability to study women 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.

[4]The PNADC is conducted by the Brazilian Institute of Geography and Statistics (IBGE), a federal agency under the Ministry of Planning and Budget.

[5]See Donovan, Lu and Schoellman (2023), which compares surveys across 48 countries. Table A3 and Table A6 in the paper.

job changes, retirements, or informal arrangements. This definition generates a large and plausibly exogenous variation in parental labor income—around 60% one year after the shock—consistent with patterns observed in studies using administrative data and mass layoff events for identification. The treatment group includes youth aged 14 to 24 whose parent experiences a job loss while the other parent remains employed. The control group consists of youth whose parents remain continuously employed or whose displacement occurs after the observation window (not-yet-treated). Parents and children are identified based on their household position in the survey.

The results show that parental job loss leads to a statistically significant increase in youth labor supply. On average, participation rises by 10.1 percentage points in the four quarters following displacement, corresponding to a 23.9% increase relative to the baseline mean of 42.2%. The effect is stronger among older youth, who experience a 35% increase relative to their baseline. The effect on employment is smaller—about 17%—indicating that part of the increased labor market activity reflects unsuccessful job search. Wages and hours worked also respond positively, with average increases of 14.7% and 15%, respectively. The consistency of these results across different labor outcomes mitigates concerns about non-random measurement error. These effects are concentrated among youth who were previously out of the labor force (extensive margin), rather than among those already working who increased their hours (intensive margin).

To shed light on the quality of youth employment following parental job loss, I examine the type of jobs undertaken by them. The increase in youth labor supply following displacement is concentrated in informal employment, particularly in unregistered jobs without formal contracts. In contrast, formal employment rises more gradually, and self-employment remains largely unaffected. I interpret that informal jobs act as a low-barrier entry point, allowing youth to respond quickly to income shocks, though often at the cost of lower job quality. 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—early shocks may force youth into lower-quality employment paths.

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 restrict 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.

To explore the broader implications of job loss, I also examine its effects on youth higher education outcomes. I find that parental displacement leads to a decline of approximately 5% in college attendance among youth aged 18 to 24. This outcome has previously been studied only in the U.S. context, where evidence points to no significant effect.[6] Brazil provides a particularly relevant institutional setting to understand how financial pressure at home affects college students. In particular, the higher education system combines a tuition-free public sector—closely aligned with the European model—with a large private sector, where enrollment is typically financed by household income or student loan programs, resembling aspects of the U.S. system. Disaggregating the effects reveals that the decline is concentrated among students in private universities, where attendance drops by up to 10 percentage points within one year of the shock. In contrast, attendance in public universities falls in the immediate quarter but recovers quickly, with estimates statistically indistinguishable from zero thereafter.[7]

The results in this dissertation point to household income loss as the primary mechanism behind youth responses to parental job displacement. As shown in Figure 5.1, parental earnings drop sharply upon separation and remain approximately 60% below pre-shock levels one year later. When estimating effects by pre-displacement income decile, significant behavioral responses are concentrated among youth in the bottom decile, while effects at the top are small and statistically indistinguishable from zero. In a setting where formal insurance mechanisms—such as credit—are limited, these findings suggest that low-income households face heightened liquidity constraints following displacement. This aligns with recent evidence from Corado et al. (2024) in Brazil, who document deteriorating credit conditions after job loss, such as reduced credit card limits. In this context, youth appear to take on an informal insurance role: they increase labor market participation and, in some cases, reduce college attendance to help buffer the household against income loss.

Related Literature.

[6] Hilger (2016) finds no significant effect of parental job loss on college attendance among low-income students in the U.S., attributing this to the availability of generous federal grant and loan programs for this group.

[7] A limitation of this analysis is the relatively small sample size, which results in wide confidence intervals. As a result, it is not possible to definitively identify underlying mechanisms.

This dissertation 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, Telle and Votruba (2011)), or long-term outcomes like children's future earnings (Oreopoulos, Page and Stevens (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, Panier and Tojerow (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 focus on other outcomes. Fontes et al. (2024), using a more comparable identification strategy here, 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. Maio and Nisticò (2019) studies 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. Britto, Melo and Sampaio (2023) also focuses on early educational outcomes for children aged 9–16, using large-scale administrative data from Brazil, and finds increases in school dropout and age-grade distortion of up to 1 and 2 percentage points, respectively.[8]

This dissertation differs from the existing literature by focusing on youth outcomes, particularly labor market behavior and higher education enrollment - two margins that are especially salient in a context like Brazil. 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

[8]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, Lam and Levison (2007) show that during economic crises in Brazil, father's job loss is correlated with higher school dropout rates among children. Oliveira, Rios-Neto and Oliveira (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.

financially dependent on their families. There is no major nationwide cash transfer program targeted at youth in this age group, with the exception of Pé de Meia, introduced only recently (in 2024). 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.

Furthermore, that is a growing literature that has interest in youth-targeted policies in developing countries. Recent contributions show that interventions such as cash transfers, vocational training, and mentorship can shape job search behavior and improve employment outcomes among disadvantaged youth (Bandiera et al. (2023); Banerjee and Sequeira (2023); Alfonsi et al. (2020); Abebe et al. (2021)). In Brazil, Machado, Szerman and Neto (2025) finds that marginal increases in Bolsa Família benefits for youth affect both formal employment and school enrollment. While these studies typically examine positive shocks—like cash transfers—this paper adds by exploring how youth respond to an unexpected and negative shock. The results show that youth transitions are highly sensitive to household income, with clear short-run effects on labor market entry, informality, and college persistence. Together, these findings offer new insights into how household financial instability can shape the life paths of disadvantaged youth.

Finally, this dissertation also makes a contribution to a growing empirical literature that investigates smoothing mechanisms following job loss under liquidity constraints. While much of this literature focuses on formal insurance mechanisms—such as credit access (Corado et al. (2024)) or severance payments (Gerard and Naritomi (2021))—I explore empirically an informal margin of adjustment: the labor supply response of other household members. This channel has received increasing theoretical attention in this context. In particular, Gerard and Naritomi (2021) develops a dynamic model of job search and consumption under liquidity constraints that extends prior frameworks by incorporating self-insurance through informal work or added-worker effects. Building on this insight, my study provides direct empirical evidence that parental job displacement induces labor supply responses among youth[9], highlighting a form of added worker effect that may carry intergenerational

[9]The added-worker effect is well documented in the literature, particularly in high-income settings and for wives labor supply responses. More recently, Halla, Schmieder and Weber (2020) offered the first causal evidence on this margin, isolating the effect on wives using a difference-in-differences strategy and administrative data from Austria. The study finds modest impacts. In contrast, evidence from developing countries remains limited, with a few studies examining correlations between transitions into non-employment and adjustments by other household members, generally finding positive responses (Gonzaga and Reis (2011); Oliveira, Rios-Neto and Oliveira (2014)).

consequences.

2
Institucional 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.

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.[1].

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.[2] The notice period and the unemployment insurance duration depend on the employee's tenure and total contribution

[1]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.

[2]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.

time.[3] 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, Maloney and Mizala (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 Rocha, Pero and Corseuil (2019) shows that estimates for 2013 indicate the continuation of a high level at 50%. In a more recent study, Britto, Pinotti and Sampaio (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, Lu and Schoellman (2023) and Gomes, Iachan and Santos (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 an 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,

[3] 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.

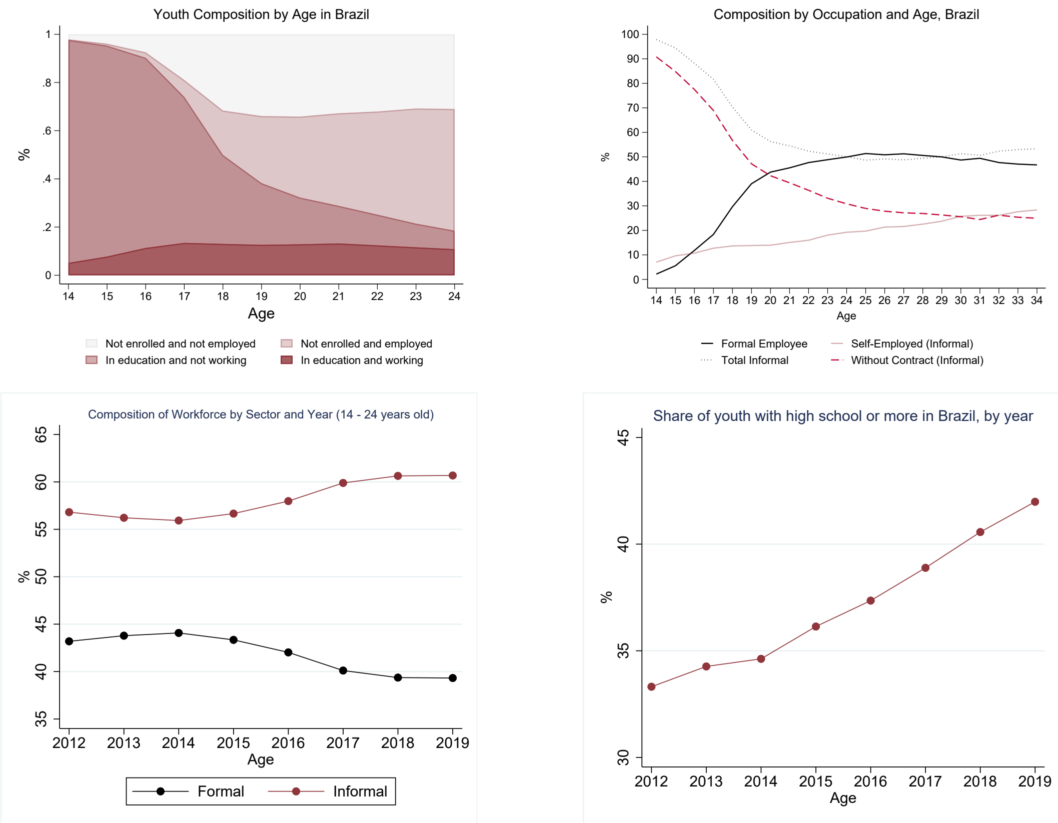
Herkenhoff and Phillips (2024). Similarly, Hilger (2016) shows that parental job loss in the US does not significantly affect children, aligning with the fact that in these countries, the impacts of job loss on credit are minimal.

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.[4]

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

Figure 2.1: 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 school is mirrored by a strong increase in labor force participation, particularly in informal employment (Panel B).[5]. 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,

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

with around 60% of employed youth aged 14–24 working informally throughout the period.

3
Data Sources and Descriptive Evidence

3.1
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)[1]. The PNADC data is advantageous in our context because it encompasses both the formal and informal sectors 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 2.1), which are not recorded in administrative data by definition. 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 A.2 in the Appendix[2].

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. [3] To map individuals across surveys and construct an individual-level panel, I use the advanced identification.[4]

[1]The PNADC quarterly data is available from at IBGE website and it is publicly available through this link.

[2]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*).

[3]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.

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

Attrition. A concern in my analysis is attrition in the longitudinal sample.[5] Throughout this study, I show that individuals with more 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 A.3). Nevertheless, the bias introduced by attrition is likely to be small. As shown in Figure A.3 and Figure A.1.2, the observable characteristics of individuals who remain in the sample and those who attrit are relatively similar.

I cannot test whether attrition differs between treatment and control groups. Therefore, 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[6]. I also incorporate the non-response weights provided by IBGE in all regressions (Variable *V1028*). 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.

3.2 Sample Selection

Step 1: Identifying Parents. I do not have access to a direct measure of biological filiation. Instead, I rely on the household identifier and the position of each individual in that household, as Maio and Nisticò (2019) and Fradkin, Panier and Tojerow (2019) do. Specifically, the children are identified as "the child of the head and the spouse of the household". [7] 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

[5]The attrition rate for constructing the individual panel is 69.1% (5ª interview). Despite being high, this is a satisfactory outcome given the absence of id identifiers and the four-quarter gap between interviews. For reference, annual attrition rates in the former PME survey averaged around 50% (JÚNIOR, SILVA and VEIGA (2016)).

[6]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.

[7]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).

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 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[8], and (iii) did not search for another job in the previous quarters[9]. 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). Doornik, Schoenherr and Skrastins (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.

[8] I use the variable *VD4002*, which follows the definition of unemployment of the IBGE. 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.

[9] I use the variable V40761, V40762 and V40763, which records the length of time (in months) an individual unemployed has been searching for work. Figure A.1 in the Appendix shows the distribution of this variable for displaced individuals. Over 85% of individuals declared having searched for work 0—3 months at the quarter of displacement, lending support to the identifying assumption.

Finally, unlike many studies in the job loss literature (e.g. Jacobson, LaLonde and Sullivan (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, Pinotti and Sampaio (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 findings remain largely consistent.

Despite these restrictions, I recognize that some voluntary and anticipated separations may persist. Some factors leading to unemployment, such as quitting to study for a public exam, for example, may not be captured. In the results section, I provide evidence that my definition of job loss is associated with a sharp and unanticipated drop in labor income, suggesting that potential cases of strategic separation are unlikely to be a concern.

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.

3.3 Descriptives

Figure 3.1: Descriptive Evidence: Main Outcomes Trends Before and After Treatment

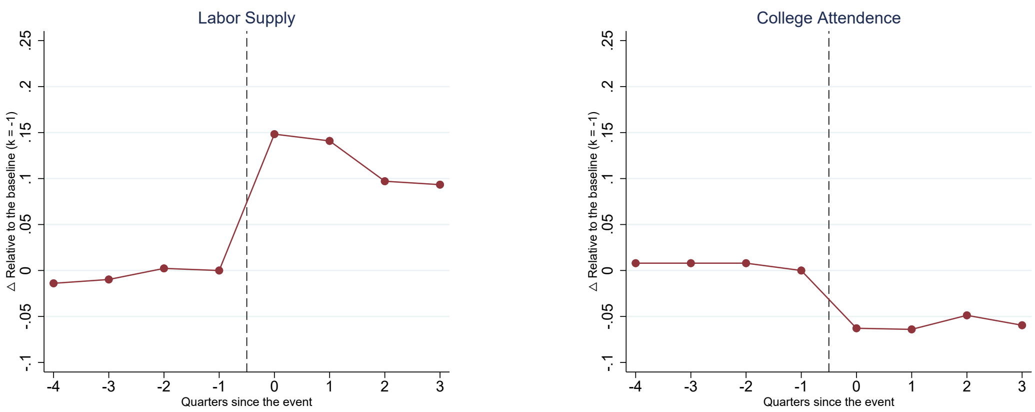


Figure 3.1 displays descriptive trends for the two main outcomes of interest: labor supply and college attendance. The graphs show average between treatment group across quarters, normalized to quarter −1 (the period immediately preceding parental job loss). Labor supply appears to increase following the shock, while college attendance declines around the same period — suggesting shifts in behavior that may be associated with the treatment. This visualization provides an initial, non-parametric look at the dynamics of these outcomes surrounding the event. Following practices in the difference-in-differences literature, I also assess covariate balance both in levels and in pre-treatment trends, as recommended by Baker et al. (2025). Specifically, I examine whether the treatment and control groups are comparable in terms of observed baseline characteristics and whether trends in these covariates evolve similarly over time before treatment.

Figure 3.2: Covariate Balance Statistics: Trends Before and After Treatment

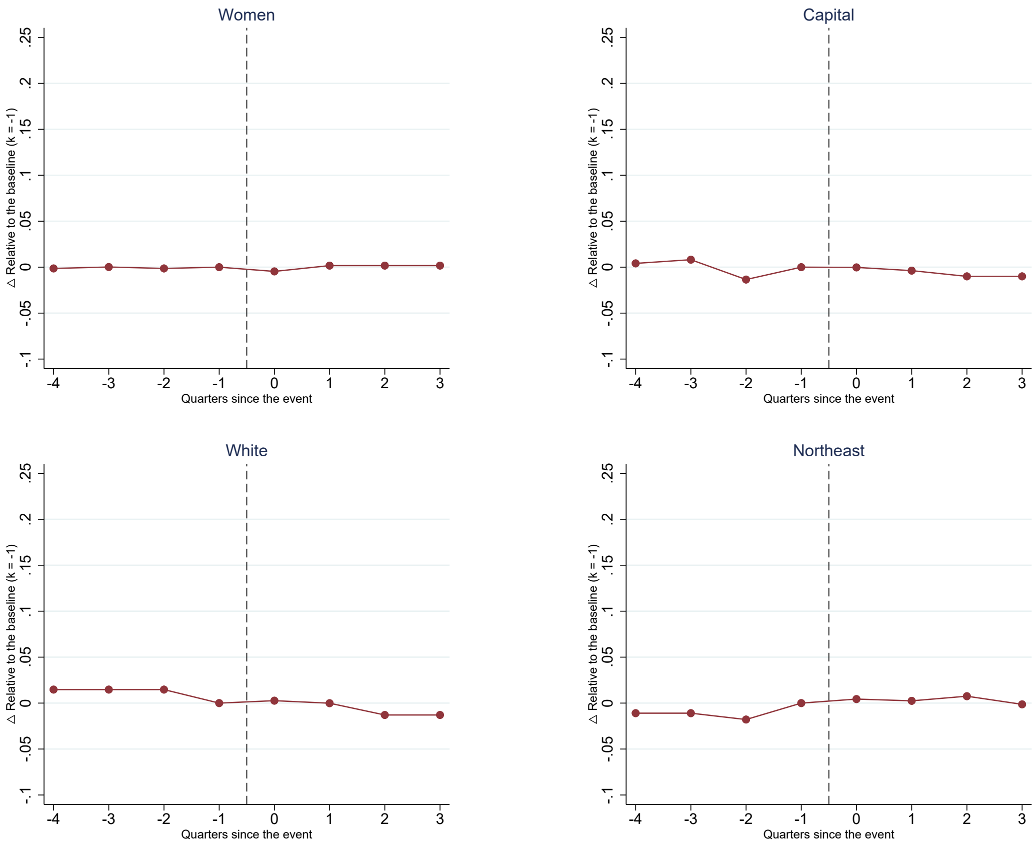


Table 3.1 displays baseline characteristics for individuals in the treatment and control groups, along with their standardized differences. Most variables exhibit small differences across groups. The only exception is parental age, which slightly exceeds the threshold. This is not surprising given the structure of the Brazilian labor market, where younger workers tend to face higher turnover and are therefore more likely to experience job displacement. In addition, Figure 3.2 presents pre-treatment trends in a set of key covariates. The visual evidence supports the parallel trends assumption: pre-treatment covariate changes are relatively flat and similar across groups, with no clear divergence prior to the shock. This pattern suggests that any post-treatment divergence in outcomes is more plausibly attributable to the treatment itself rather than to underlying differences in pre-treatment dynamics.

Table 3.1: 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 Salary	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 Salary	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

4
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)[1] methodology to estimate dynamic treatment effects.

4.1
Estimation and Aggregation

Let $i \in \{1, 2, ..., N\}$ 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[2]. 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:

$$ATT(g, t) := \mathbb{E}[Y_t(1) - Y_t(0) \mid G_g = 1] \tag{4-1}$$

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:

$$\widehat{ATT}^{\text{type}}(g, t) = \frac{\sum_i \Delta Y_{i,g-1,t} 1\left\{G_i^{\text{type}} = g\right\}}{\sum_i 1\left\{G_i^{type} = g\right\}} - \frac{\sum_i \Delta Y_{i,g-1,t} C_i}{\sum_i C_i} \tag{4-2}$$

Where $\Delta Y_{ig-1,t} \equiv Y_{i,t} - Y_{i,g-1}$ is the evolution of outcome Y in a given

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

[2]Note that $t = 0$ represent 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.

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 ($e = t-g \in \{-3:3\}$)[3]. To evaluate magnitude and heterogeneities, I combine the post-treatment estimates ($e \in \{0:3\}$) 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 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 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 [4].

4.2 Identification

The estimator in Equation 4-2 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

[3] 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.

[4] 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

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 5.1).

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.[5]

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 4-2. 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[6] is that I observe youth labor market outcomes before and after job loss events, 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 3.1 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

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

[6] 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, Page and Stevens (2008), Bratberg, Nilsen and Vaage (2008), Rege, Telle and Votruba (2011)). The key identifying assumption is that job loss resulting from plant closures is effectively random when controlling for observable characteristics.

loss stemming from mass layoffs or plant closures,[7] 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, Pinotti and Sampaio (2022); Britto, Melo and Sampaio (2023))[8]. In Section 5.1, 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.

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 4-2 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

[7]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 highlight the importance of comparing pre- and post-treatment dynamics to strengthen causal inference.

[8]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.

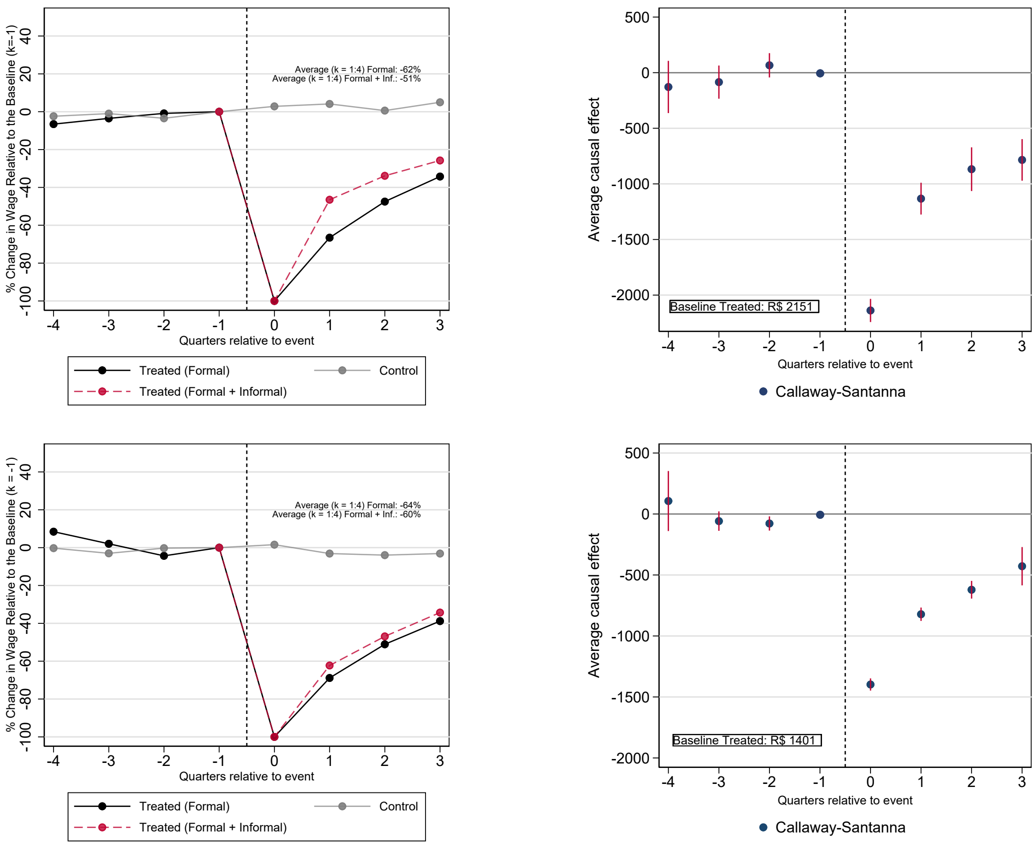
within individuals. I also tested clustering at the household level, and the results remain robust.

5
Results

5.1
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. In line with the literature, job loss causes substantial income losses for both mother and father, as shown in the graphs of Figure 5.1.

Figure 5.1: 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 graphs on the left display simple averages of the percentual income variation relative to the baseline period ($k = -1$). The graphs on the right present the dynamic treatment effects, estimated using the difference-in-differences approach specified in equation 4-2, along with 95% confidence intervals. Informal employment is defined as self-employed or workers without a formal labor contract (CLT).

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, Pinotti and Sampaio (2022))[1].

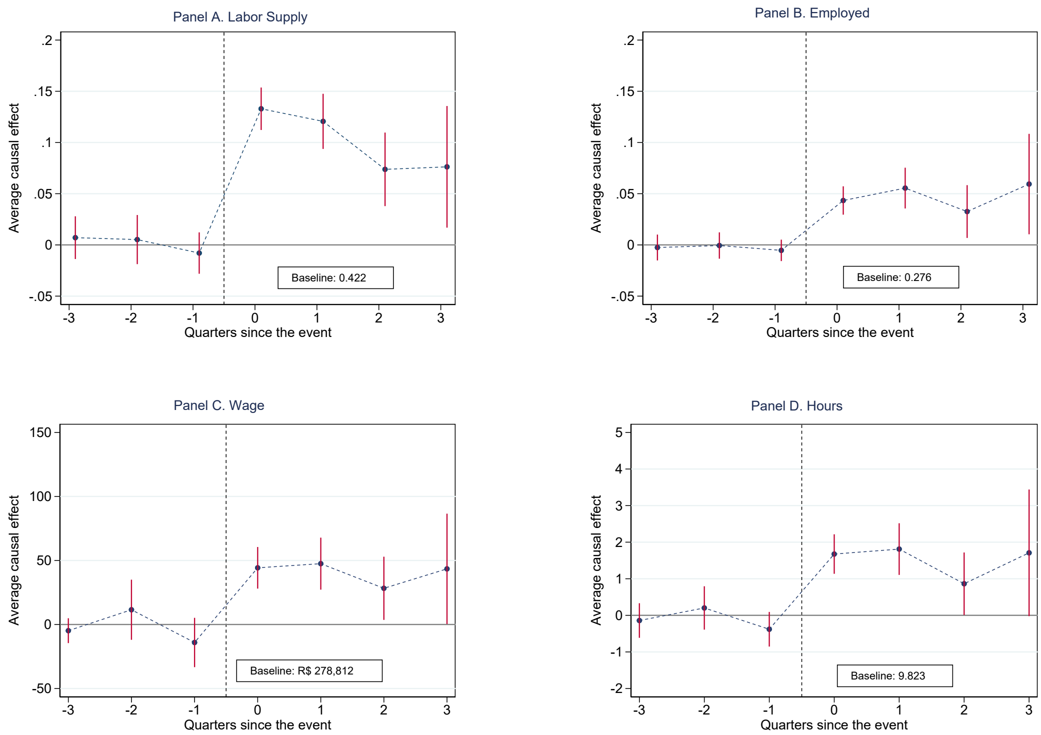
When considering the informal sector, income losses are 51% for fathers and 60% for mothers. This finding is consistence with the role of the informal sector as a buffer against economic shocks (Ponczek and Ulyssea (2020)). The graphs on the right provide a more detailed picture of income dynamics, incorporating a 95% confidence interval and presenting the dynamic treatment effects using the specification in equation 4-2. 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.

5.2
Effect of Parental Job Loss on Youth Labor Market Outcomes

[1]They found a 65% formal labor income drop for men in the first year, while I found 62%. They used a sample of individuals aged 20 to 50 years, while I used individuals aged 25 to 59 years.

5.2.1
Youth Labor Supply and Employment

Figure 5.2: Effect of Job Loss on Youth Labor Market Outcomes



Note: The figures present dynamic treatment effects estimated using the event-study specification described in Equation (1), with 95% confidence intervals. The treatment group consists of individuals whose parents were employed in the private sector and subsequently became unemployed in one of the following survey waves. The control group includes individuals whose parents remained continuously employed throughout all observed quarters. The outcomes analyzed include labor force participation (Panel A), employment status (Panel B), monthly labor earnings (Panel C), and hours worked (Panel D). .

Extensive margin. I now turn to the analysis of youth labor market outcomes, beginning with labor supply.[2] I estimate the event-study specification presented in Equation 4-2. Panel A of Figure 5.2 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[3]. Prior to the shock, there are

[2] 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.

[3] 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,

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 A.4 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 4-2 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. [4]

Panels C and D provide further insights by analyzing employment responses through alternative measures: hours worked and wages. Specifically, Table A.4 shows that parental job loss leads to an average increase of R$40.9 in wages, corresponding to a 14.7% rise relative to the baseline average wage of R$278.81[5]. 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 4-2 is that the gap in youth labor supply rates emerges only after parental displacement. This suggests no evidence of

(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.

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

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

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 A.4 in 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[6]. 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.

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, Schmieder and Weber (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.

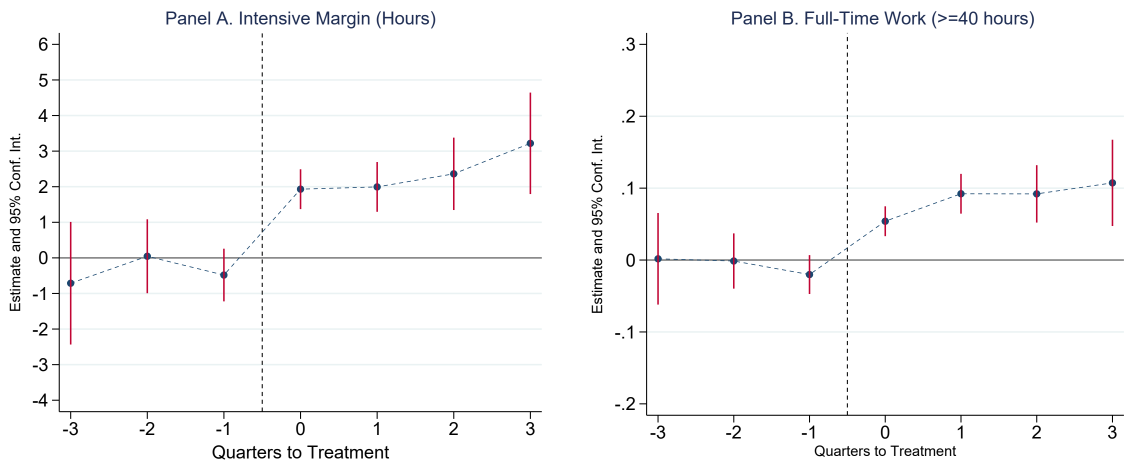
In our context, 26% of youth in the sample were already employed at the time of parental job loss. This allows us to go beyond analyzing market entry and to investigate whether labor supply adjustments also occur at the intensive margin. Specifically, we examine whether previously employed youth increase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

Figure 5.3 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

[6]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.

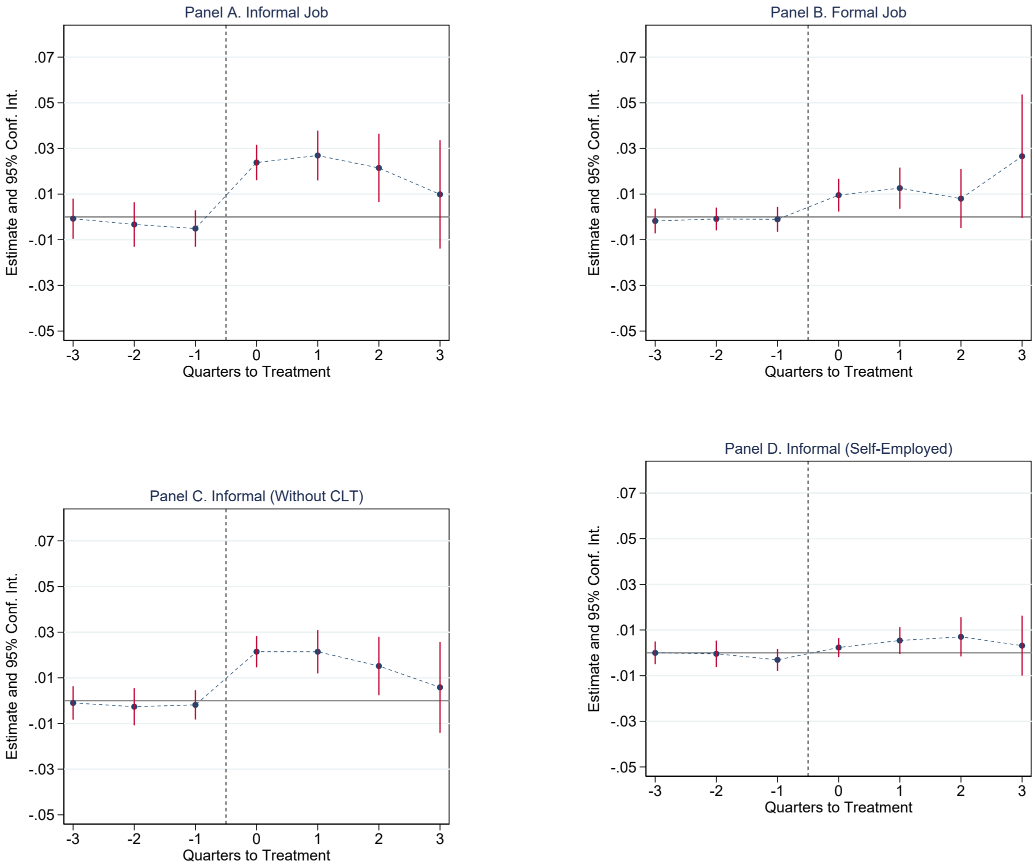
significantly increasing their hours.

Figure 5.3: Effect of Parental Job Loss on Hours Worked



5.2.2 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, Ham and Viollaz (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.



Note: This figure shows dynamic treatment effects of parental job loss on youth employment type, estimated using the difference-in-differences specification described in Equation (1). Each panel reports event-study coefficients with 95% confidence intervals. The control group consists of youth whose parents remained continuously employed. Panel A presents the effect on informal employment, while Panel B shows the response for formal jobs. Panels C and D decompose the informal response into unregistered jobs (Panel C) and self-employment (Panel D).

Figure 5.4: Effect of Job Loss on Parental Labor Income

Figure **??** 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; 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).

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, Ham and Viollaz (2012)).

Heterogeneity with 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 5.1 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.

5.3 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 5.5 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

Table 5.1: Employment Effects by Age and Sector

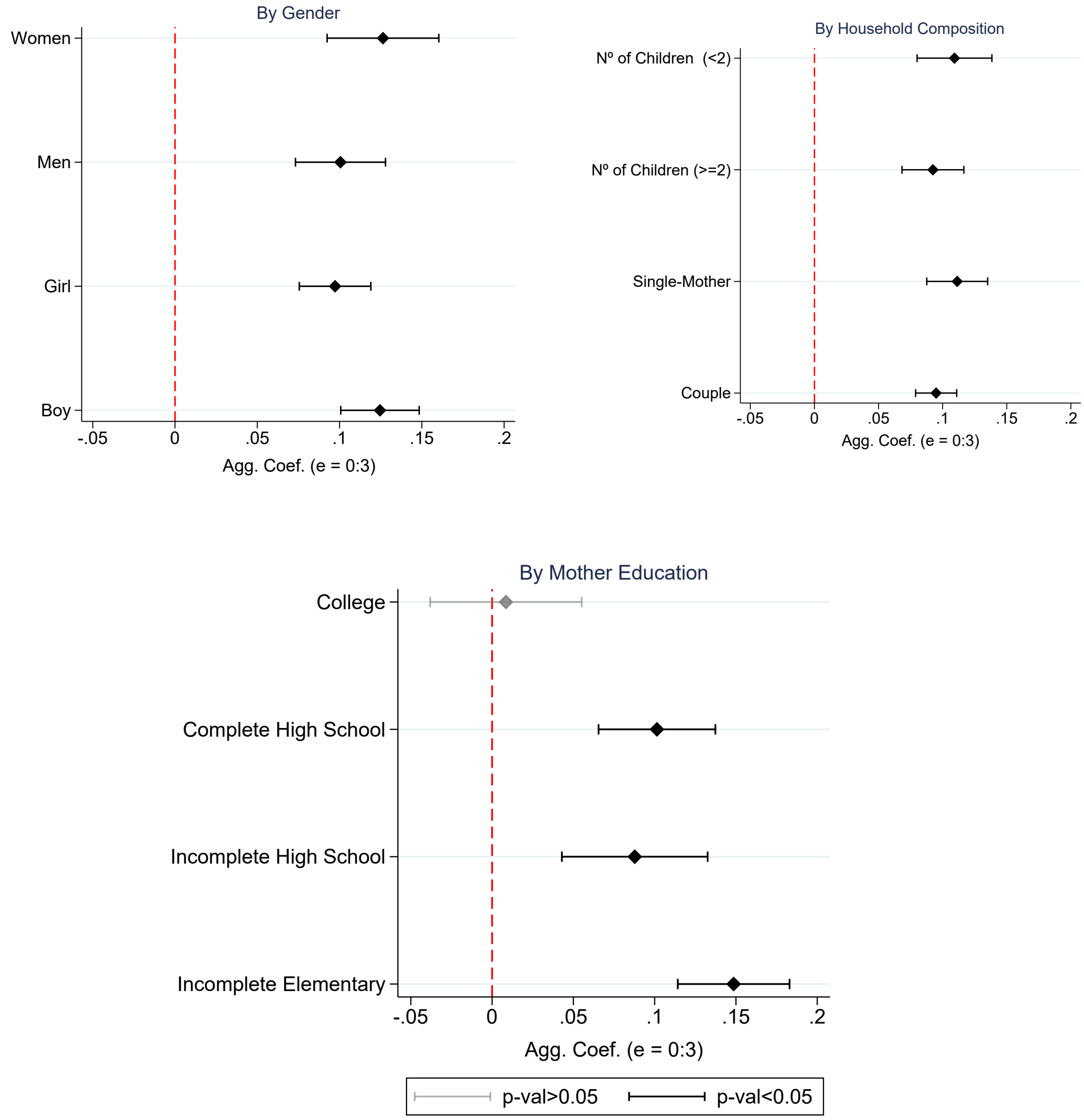
Sector	Employment Type	14-20	P(y | Employed)	21-24	P(y | Employed)
	y = Any Work	0.034***	100%	0.091***	100%
		(0.005)		(0.027)	
Formal	y = With CLT	0.010***	29.4%	0.047**	51.6%
		(0.003)		(0.018)	
	y = Self-Employed	0.004	11.8%	0.014	15.4%
		(0.002)		(0.008)	
Informal	y = Without CLT	0.020***	58.9%	0.030	33.0%
		(0.004)		(0.019)	

Significance levels: *** p<0.01, ** p<0.05, * p<0.1. "Any Work" indicates whether the individual was employed in any sector. "With CLT" represents formal employment with a labor contract. "Without CLT" represents informal employment without a formal contract. "Self-Employed" includes individuals working independently without an employer. $P(y|Employed)$ is computed as the conditional probability of being in a specific employment type given that the individual is employed: computed as $P(y|\text{Employed}) = P(y \cap \text{Employed})/P(\text{Employed})$, where $P(y \cap \text{Employed})$ is the share of individuals in employment type y, and $P(\text{Employed})$ is the total employment rate within the respective age group.

increase in labor supply than girls, the difference is not statistically significant.

By contrast, the effects vary considerably with the level of parental education and age. Figure 5.5 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)).

Figure 5.5: Heterogeneous Effects of Parental Job Loss on Youth Labor Market Outcomes According to Family Characteristics

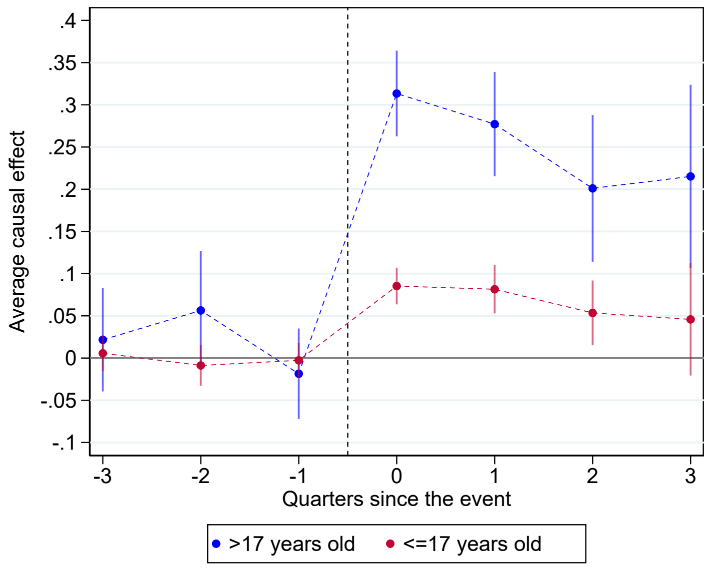


Note: This figure plots aggregated treatment effects and 95% confidence intervals for the impact of parental job loss on youth labor force participation, across subgroups defined by individual and household characteristics. Estimates are based on a DiD framework using individual-level clustered standard 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; and Panel C by maternal education level. Each point represents the average post-treatment effect on labor force participation for the corresponding subgroup.

Figure 5.6 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 (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.

Figure 5.6: Effect of Parental Job Loss on Youth Labor Supply, By Age



Note: The figures present dynamic treatment effects estimated using the event-study specification described in Equation (1), with 95% confidence intervals. The treatment group consists of individuals whose parents were employed in the private sector and subsequently became unemployed in one of the following survey waves. The control group includes individuals whose parents remained continuously employed throughout all observed quarters.

5.4 Additional Results: 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 analyze this relationship, I focus on individuals aged 18 to 24 who, in their first interview, report being enrolled in higher education. College attendance is measured using variable V3003, while the classification between public and private institutions relies on V3002a, available just from 2017 onward. Due to sample size limitations, confidence intervals are wide.

Figure 5.7: Effect of Parental Job Loss on College Attendance

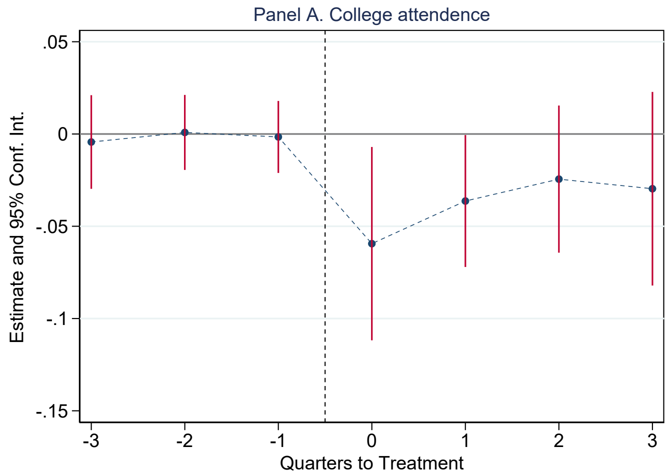


Figure 5.8: Effect of Parental Job Loss on College Attendance, By Type of Institution

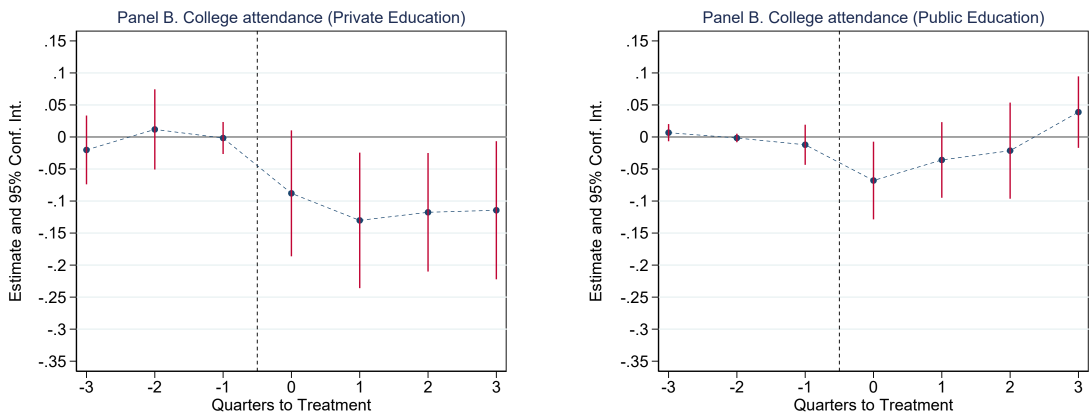


Figure 5.7 shows the overall impact of parental job loss on college attendance among youth aged 18 to 24. In the quarters following the shock, there is a decline in college attendance of approximately 5 percentage points relative to the baseline level observed before the displacement. The effect becomes less pronounced from the second quarter onward.

Figure 5.8 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's 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.[7] 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.[8] My findings suggest

[7]ferreyra2017 and ristoff2014 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. mello2022 argues that the simultaneous implementation of a centralized admissions system and quota policies may have limited the effectiveness of these measures in broadening access.

[8]Fradkin, Panier and Tojerow (2019) do not analyze college enrollment, as university

that the effects of parental job loss on college attendance observed in high-income contexts may not extend to settings with weaker credit markets.

tuition in Belgium is heavily subsidized, reducing the financial impact of parental job loss. They reference Hilger (2016) as an upper bound.

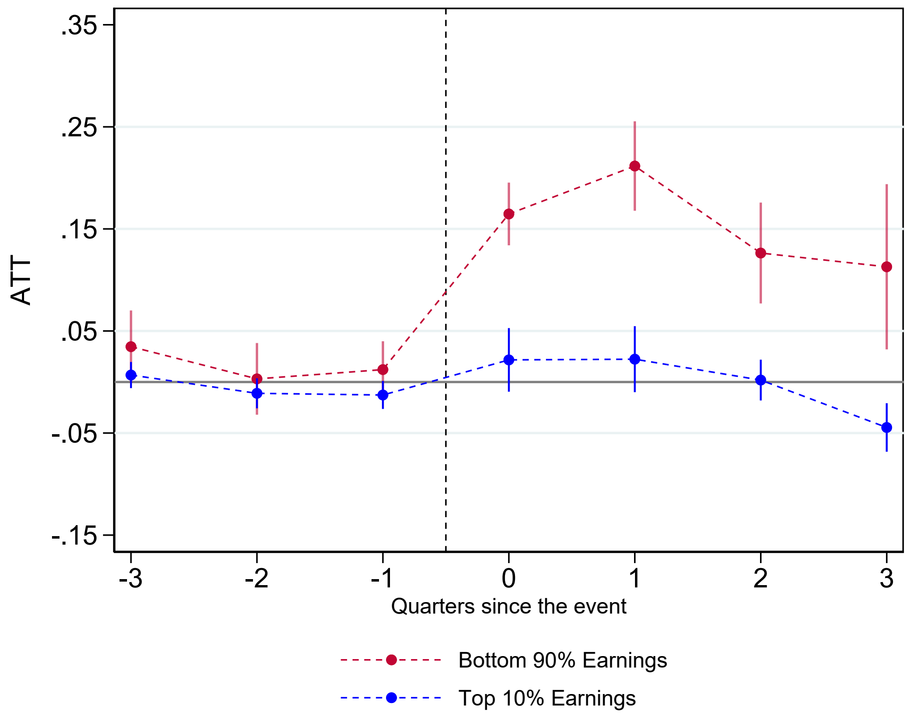
6
Mechanisms

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 and annoy their children (and vice versa), then 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)). 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, Komatsu and Menezes-Filho (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 6.1 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.

Figure 6.1: 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).

The decline in college attendance (Section 5.4), particularly when disaggregated by institution type, also provides supporting evidence for this mechanism. The drop is more pronounced and persistent among students enrolled in private institutions, where tuition payments are closely tied to household resources. In contrast, students attending tuition-free public universities experience a short-lived decline in enrollment immediately after the shock, but attendance recovers shortly thereafter. While I cannot completely rule out alternative explanations—such as psychological stress within the household—the strong concentration of effects among low-income youth reinforces the interpretation that financial distress is the primary mechanism at play.

7
Conclusion

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 dissertation 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. Future work can further explore whether these short-run adjustments persist, and how they influence long-term outcomes.

8
Bibliography

ABEBE, G. et al. Anonymity or distance? job search and labour market exclusion in a growing african city. **The Review of Economic Studies**, Oxford University Press, v. 88, n. 3, p. 1279–1310, 2021.

ALFONSI, L. et al. Tackling youth unemployment: Evidence from a labor market experiment in uganda. **Econometrica**, Wiley Online Library, v. 88, n. 6, p. 2369–2414, 2020.

BAKER, A. et al. Difference-in-differences designs: A practitioner's guide. **arXiv preprint arXiv:2503.13323**, 2025.

BAKER, A. C.; LARCKER, D. F.; WANG, C. C. How much should we trust staggered difference-in-differences estimates? **Journal of Financial Economics**, Elsevier, v. 144, n. 2, p. 370–395, 2022.

BANDIERA, O. et al. **The search for good jobs: evidence from a six-year field experiment in Uganda**. [S.l.], 2023.

BANDIERA, O. et al. Young adults and labor markets in africa. **Journal of Economic Perspectives**, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203-2418, v. 36, n. 1, p. 81–100, 2022.

BANERJEE, A.; SEQUEIRA, S. Learning by searching: Spatial mismatches and imperfect information in southern labor markets. **Journal of development economics**, Elsevier, v. 164, p. 103111, 2023.

BERNIELL, I. et al. Gender gaps in labor informality: The motherhood effect. **Journal of Development Economics**, Elsevier, v. 150, p. 102599, 2021.

BHALOTRA, S. R. et al. Job displacement, unemployment benefits and domestic violence. **The Review of Economic Studies (forthcoming)**, 2025.

BLATTMAN, C.; FIALA, N.; MARTINEZ, S. Generating skilled self-employment in developing countries: Experimental evidence from uganda. **The Quarterly Journal of Economics**, MIT Press, v. 129, n. 2, p. 697–752, 2014.

BRATBERG, E.; NILSEN, Ø. A.; VAAGE, K. Job losses and child outcomes. **Labour Economics**, Elsevier, v. 15, n. 4, p. 591–603, 2008.

BRAXTON, J. C.; HERKENHOFF, K.; PHILLIPS, G. M. Can the unemployed borrow? implications for public insurance. **Journal of Political Economy**, The University of Chicago Press Chicago, IL, v. 132, n. 9, p. 3025–3076, 2024.

BRAZIL, O. Oecd employment outlook - investing in youth: Brazil, 2014. 2014.

BRITTO, D. G.; MELO, C.; SAMPAIO, B. The kids aren't alright: Parental job loss and children's education. IZA Discussion Paper, 2023.

BRITTO, D. G.; PINOTTI, P.; SAMPAIO, B. The effect of job loss and unemployment insurance on crime in brazil. **Econometrica**, Wiley Online Library, v. 90, n. 4, p. 1393–1423, 2022.

CABANAS, P.; KOMATSU, B. K.; MENEZES-FILHO, N. A. Crescimento da renda e as escolhas dos jovens entre os estudos e o mercado de trabalho. **ENCONTRO NACIONAL DA ASSOCIAÇÃO NACIONAL DE PÓS-GRADUAÇÃO EM ECONOMIA**, 2014.

CALLAWAY, B.; SANT'ANNA, P. H. Difference-in-differences with multiple time periods. **Journal of econometrics**, Elsevier, v. 225, n. 2, p. 200–230, 2021.

CHAISEMARTIN, C. D.; D'HAULTFOEUILLE, X. Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: A survey. **The econometrics journal**, Oxford University Press, v. 26, n. 3, p. C1–C30, 2023.

CORADO, N. et al. Leavers and stayers after mass layoffs: Labor and credit market outcomes. Working Paper. 2024.

CORSEUIL, C. H. et al. Youth labor market in brazil through the lens of the flow approach. In: **Proceedings of the 41st brazilian economics meeting, ANPEC**. [S.l.: s.n.], 2013.

CORSEUIL, C. H. L. et al. A rotatividade dos jovens no mercado de trabalho formal brasileiro. Instituto de Pesquisa Econômica Aplicada (Ipea), 2014.

COUCH, K. A.; PLACZEK, D. W. Earnings losses of displaced workers revisited. **American Economic Review**, American Economic Association, v. 100, n. 1, p. 572–589, 2010.

CRUCES, G.; HAM, A.; VIOLLAZ, M. Scarring effects of youth unemployment and informality: Evidence from brazil. **Unpublished paper.**, 2012.

DAL-RI, F. What does it take to be a business owner? evidence from transitions from job loss. 2024.

DONOVAN, K.; LU, W. J.; SCHOELLMAN, T. Labor market dynamics and development. **The Quarterly Journal of Economics**, Oxford University Press, v. 138, n. 4, p. 2287–2325, 2023.

DOORNIK, B. V.; SCHOENHERR, D.; SKRASTINS, J. Unemployment insurance, strategic unemployment, and firm-worker collusion. **Central Bank of Brazil, Research Department**, n. 483, 2018.

DUFLO, E. et al. **Intergenerational impacts of secondary education: experimental evidence from Ghana**. [S.l.], 2024.

DURYEA, S.; LAM, D.; LEVISON, D. Effects of economic shocks on children's employment and schooling in brazil. **Journal of development economics**, Elsevier, v. 84, n. 1, p. 188–214, 2007.

ENGBOM, N. et al. Earnings inequality and dynamics in the presence of informality: The case of brazil. **Quantitative Economics**, Wiley Online Library, v. 13, n. 4, p. 1405–1446, 2022.

FINAMOR, L. Labor market informality, risk, and insurance. working paper. 2024.

FLAAEN, A.; SHAPIRO, M. D.; SORKIN, I. Reconsidering the consequences of worker displacements: Firm versus worker perspective. **American Economic Journal: Macroeconomics**, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203-2425, v. 11, n. 2, p. 193–227, 2019.

FONTES, L. F. et al. Economic distress and children's mental health: Evidence from the brazilian high-risk cohort study for mental conditions. **The Economic Journal**, Oxford University Press, v. 134, n. 660, p. 1701–1718, 2024.

FRADKIN, A.; PANIER, F.; TOJEROW, I. Blame the parents? how parental unemployment affects labor supply and job quality for young adults. **Journal of labor economics**, University of Chicago Press Chicago, IL, v. 37, n. 1, p. 35–100, 2019.

GERARD, F.; GONZAGA, G. Informal labor and the efficiency cost of social programs: Evidence from unemployment insurance in brazil. **American Economic Journal: Economic Policy**, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203-2425, v. 13, n. 3, p. 167–206, 2021.

GERARD, F.; NARITOMI, J. Job displacement insurance and (the lack of) consumption-smoothing. **American Economic Review**, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203, v. 111, n. 3, p. 899–942, 2021.

GOMES, D. B.; IACHAN, F. S.; SANTOS, C. Labor earnings dynamics in a developing economy with a large informal sector. **Journal of Economic Dynamics and Control**, Elsevier, v. 113, p. 103854, 2020.

GOMES, M.; HIRATA, G. Determinantes da evasão no ensino superior: uma abordagem de riscos competitivos. **Pesquisa e Planejamento Econômico**, v. 52, n. 3, 2022.

GONZAGA, G.; MALONEY, W. F.; MIZALA, A. Labor turnover and labor legislation in brazil [with comments]. **Economia**, JSTOR, v. 4, n. 1, p. 165–222, 2003.

GONZAGA, G.; REIS, M. C. Oferta de trabalho e ciclo econômico: os efeitos trabalhador adicional e desalento no brasil. **Revista Brasileira de Economia**, SciELO Brasil, v. 65, p. 127–148, 2011.

HALLA, M.; SCHMIEDER, J.; WEBER, A. Job displacement, family dynamics, and spousal labor supply. **American Economic Journal: Applied Economics**, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203-2425, v. 12, n. 4, p. 253–287, 2020.

HENDREN, N. Knowledge of future job loss and implications for unemployment insurance. **American Economic Review**, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203, v. 107, n. 7, p. 1778–1823, 2017.

HILGER, N. G. Parental job loss and children's long-term outcomes: Evidence from 7 million fathers' layoffs. **American Economic Journal: Applied Economics**, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203-2425, v. 8, n. 3, p. 247–283, 2016.

IMBENS, G. W.; RUBIN, D. B. **Causal inference in statistics, social, and biomedical sciences**. [S.l.]: Cambridge university press, 2015.

JACOBSON, L. S.; LALONDE, R. J.; SULLIVAN, D. G. Earnings losses of displaced workers. **The American economic review**, JSTOR, p. 685–709, 1993.

JÚNIOR, A. T.; SILVA, D.; VEIGA, A. Produção de pesos longitudinais para estimação e análise de dados da pesquisa mensal de emprego do ibge. **SIMPÓSIO NACIONAL DE PROBABILIDADE E ESTATÍSTICA**, v. 22, 2016.

MACHADO, C.; SZERMAN, C.; NETO, V. P. Too late for a change? youth unresponsiveness to cash transfers. Working Paper. 2025.

MAIO, M. D.; NISTICÒ, R. The effect of parental job loss on child school dropout: Evidence from the occupied palestinian territories. **Journal of Development Economics**, Elsevier, v. 141, p. 102375, 2019.

MARCOS, M. A. T. Grandmothers and the gender gap in the mexican labor market. **Journal of Development Economics**, Elsevier, v. 162, p. 103013, 2023.

NARITA, R. Self-employment in developing countries: A search-equilibrium approach. **Review of Economic Dynamics**, Elsevier, v. 35, p. 1–34, 2020.

OLIVEIRA, E. L. d.; RIOS-NETO, E. G.; OLIVEIRA, A. M. H. C. d. O efeito trabalhador adicional para filhos no brasil. **Revista Brasileira de Estudos de População**, SciELO Brasil, v. 31, p. 29–49, 2014.

OREOPOULOS, P.; PAGE, M.; STEVENS, A. H. The intergenerational effects of worker displacement. **Journal of Labor Economics**, The University of Chicago Press, v. 26, n. 3, p. 455–483, 2008.

OSORIO, R. G. Sobre a montagem e a identificação dos painéis da pnad contínua1. **Mercado de Trabalho**, p. 69, 2022.

PONCZEK, V.; ULYSSEA, G. Is informality an employment buffer? evidence from the trade liberalization in brazil. **Unpublished manuscript**, 2020.

REGE, M.; TELLE, K.; VOTRUBA, M. Parental job loss and children's school performance. **The Review of Economic Studies**, Oxford University Press, v. 78, n. 4, p. 1462–1489, 2011.

REIS, M. Uma análise da transição dos jovens para o primeiro emprego no brasil. **Revista Brasileira de Economia**, SciELO Brasil, v. 69, p. 125–143, 2015.

RIBAS, R. P.; SOARES, S. S. D. **Sobre o painel da Pesquisa Mensal de Emprego (PME) do IBGE**. [S.l.], 2008.

ROCHA, L. P. da; PERO, V. L.; CORSEUIL, C. H. Turnover, learning by doing, and the dynamics of productivity in brazil. **EconomiA**, Elsevier, v. 20, n. 3, p. 191–210, 2019.

ROTH, J. et al. What's trending in difference-in-differences? a synthesis of the recent econometrics literature. **Journal of Econometrics**, Elsevier, v. 235, n. 2, p. 2218–2244, 2023.

SCHMIEDER, J. F.; WACHTER, T. V.; HEINING, J. The costs of job displacement over the business cycle and its sources: evidence from germany. **American Economic Review**, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203, v. 113, n. 5, p. 1208–1254, 2023.

SKOUFIAS, E.; PARKER, S. W. Job loss and family adjustments in work and schooling during the mexican peso crisis. **Journal of Population Economics**, Springer, v. 19, p. 163–181, 2006.

SPEAR, L. P. The adolescent brain and age-related behavioral manifestations. **Neuroscience & biobehavioral reviews**, Elsevier, v. 24, n. 4, p. 417–463, 2000.

SULLIVAN, D.; WACHTER, T. V. Job displacement and mortality: An analysis using administrative data. **The Quarterly Journal of Economics**, MIT Press, v. 124, n. 3, p. 1265–1306, 2009.

WACHTER, T. V. The persistent effects of initial labor market conditions for young adults and their sources. **Journal of Economic Perspectives**, American Economic Association 2014 Broadway, Suite 305, Nashville, TN 37203-2418, v. 34, n. 4, p. 168–194, 2020.

ZIMMER, D. M. The effect of job displacement on mental health, when mental health feeds back to future job displacement. **The Quarterly Review of Economics and Finance**, Elsevier, v. 79, p. 360–366, 2021.

ZISS, R.; DICK, E. The relevance of the informal sector to youth employment and social integration. In: **Draft study report for the World Bank's Youth Employment Workshop. http://wbln0018. worldbank. org/HDNet/HDdocs. nsf/0/CF861243EAB060D185256D340 05466B2**. [S.l.: s.n.], 2003.

A
Appendix

A.1
Data

Table A.1: Summary of Restrictions by Step: Main Sample

Step	Obs.	Labor Force Participation (%)	Employed (%)	Female (%)	School Attendance (%)
(1) All children 14-20	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) With Parents aged 25-59	1,614,444	34.8	25.8	46.2	73.8
(4) Without Error in ID	1,492,794	35.0	26.1	46.4	74.1
(5) Two+ interviews	1,382,628	34.9	26.1	46.4	74.4

A.1.1
Variable Definitions

The definition of the variables below is according to IBGE.

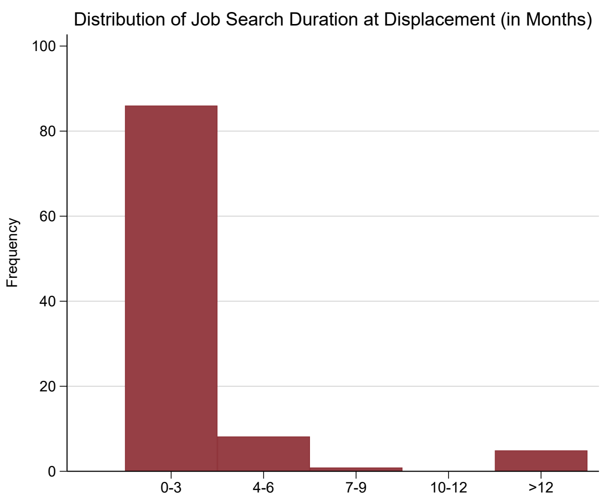


Figure A.1
Note: This figure displays the distribution of job search duration at the time of displacement, using PNADC survey data. The underlying variable aggregates three variables — V40761, V40762, and V40763 — and reports the total length of job search in months.

Table A.2: 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

Variable	**Definition**
Unemployed	The individual is considered unemployed if they meet the following three criteria: *(i)* they were not engaged in any work during the reference period; *(ii)* they were available to begin work during the reference period; and *(iii)* they actively sought employment during the reference period.
Household Head	Refers to the individual identified by household members as the primary person responsible for the household. In cases where more than one person is identified, the first person listed among the heads of the household is considered.
Job Search	Job search refers to taking deliberate actions aimed at obtaining income-generating employment, such as: *(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.
Employed	Individuals are classified as employed if they worked at least one full hour in paid employment (in cash, goods, or benefits such as housing, food, clothing, or training) or in unpaid work that helps the economic activity of a household member. This also includes individuals who were temporarily absent from paid employment.
Labor Force (LF)	This category includes individuals who were employed or unemployed.
LF Participation Rate	Defined as the percentage of individuals in the labor force relative to the total working-age population.
Non-Response Weight	This weight is made by IBGE to account for nonresponses, such as refusals, inability to contact residents, or other reasons for incomplete interviews in occupied households.

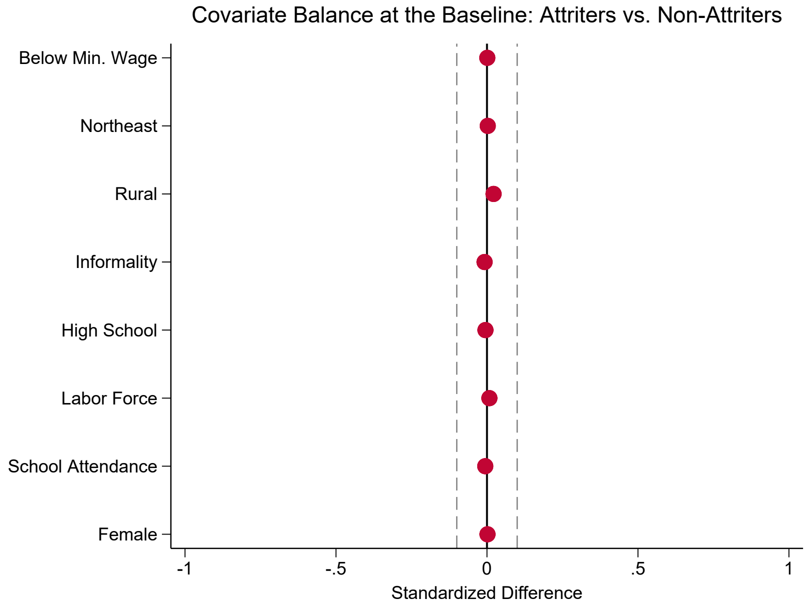
A.1.2 Attrition

Table A.3: Summary Statistics at the Baseline: 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 (%)	27.8%	72.2%

Notes: This table reports the mean values of baseline covariates (1st interview) for individuals who attrited (did not appear in the last interview) and those who remained in the sample. This rate represents the proportion of individuals who remain in the sample throughout the survey waves, using the identification algorithm proposed by Ribas and Soares (2008). The main sample consists of families with children aged 14 to 24 and household heads or spouses aged 25 to 59; only individuals who appear at least twice in the survey are included. Standard deviations are in parentheses.

Figure A.2: Covariate Balance



Note: The graph on the left presents the attrition rate across interview, calculated based on the main sample. This rate represents the proportion of individuals who remain in the sample throughout the survey waves, using the identification algorithm proposed by Ribas and Soares (2008). The main sample consists of families with children aged 14 to 24 and household heads or spouses aged 25 to 59; only individuals who appear at least twice in the survey are included. The graph on the right presents the standardized mean differences for key baseline covariates between individuals who attrited (did not appear in the last interview) and those who remained in the sample. The covariates include demographic characteristics (e.g., gender, education, and rural residence), labor market indicators (e.g., informality and labor force participation), and regional identifiers. Dashed vertical lines at -0.2 and 0.2 indicate the conventional threshold for balance, as suggested by Imbens and Rubin (2015).

A.2
Results

Table A.4: Event-Study Estimates

	Job Search	Employment		
	Labor Supply	Employed	Wage	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%
# Obs. Treated	21,689	21,689	21,689	21,689
# Obs. Control	568,719	568,719	568,719	568,719

Significance levels: *** p<0.01, ** p<0.05, * p<0.1

Table A.5: Heterogeneity By Age

	Young Adult (18-24)	Young 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

Significance levels: *** p<0.01, ** p<0.05, * p<0.1

A.3 Robustness

Figure A.3: Robustness: Other DID estimators

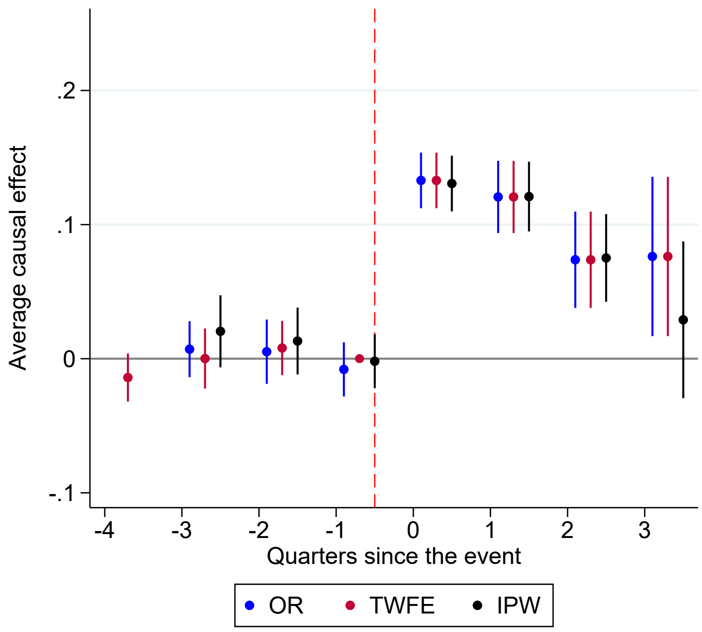


Figure A.4: Robustness: Relaxing spouse labor supply

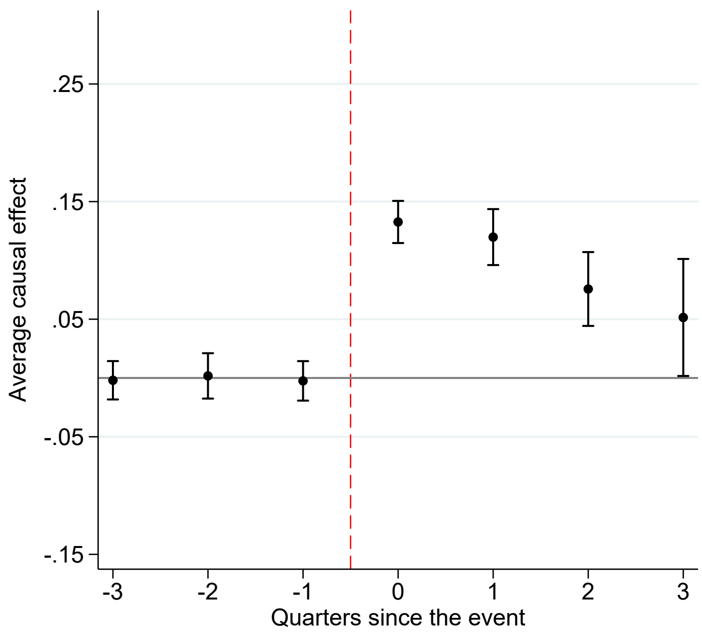


Figure A.5: Robustness: Alternative control groups