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Does Local Employment Growth Accelerate Exits From Social Assistance?

Evidence From Brazil's Conditional Cash Transfer Bolsa Familia

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Abstract

A large literature highlights the need for low- and middle-income countries to establish adaptive social safety nets responsive to labor market shifts. While much is known about safety nets' expansion during downturns, less is understood about their response to labor market recoveries. This paper examines how municipal formal employment affects the likelihood of families exiting Bolsa Familia, Brazil's means-tested cash transfer program. Survival analysis reveals that families exiting the program tend to have better-educated household heads, live in urban areas, and have fewer children. Fixed-effects estimation, combined with a shift-share instrument, shows that local employment growth leads to a small but statistically significant increase in the probability of exiting Bolsa Familia. A 10% growth in local employment raises the exit probability by 0.342 percentage points, increasing the average transition rate from 8.61% to 8.69%. These effects are concentrated in households with spare labor supply.

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1 Introduction

Social safety nets – especially in the form of conditional cash transfers (CCTs) – are essential for reducing poverty and enhancing the resilience of vulnerable populations. There is growing consensus on the need for adaptive social assistance programs that can dynamically respond to economic shocks in low- and middle-income countries (Bowen *et al.*, 2020). While substantial research has examined pathways into these programs (Bah *et al.*, 2019; Baird *et al.*, 2013; Bowen *et al.*, 2020; Coady and Parker, 2009; Grosh *et al.*, 2022) as well as the positive effects of conditionalities on beneficiaries (Baird *et al.*, 2014; Fiszbein *et al.*, 2009; Glewwe and Kassouf, 2012; Kabeer and Waddington, 2015; Lagarde *et al.*, 2007; Millán *et al.*, 2019; Oconnor, 2024), less attention has been given to the factors that facilitate beneficiaries' exits. As governments worldwide face growing budget constraints, understanding the conditions that support program graduation is critical for designing effective, dynamic, and sustainable social assistance systems.

This paper seeks to address this knowledge gap concerning program exits. First, it examines the factors that are correlated with exits from Brazil's CCT program, Bolsa Familia (BF) and finds that families exiting the program tend to have better-educated household heads, live in urban areas, and have fewer children. Second, it explores how improved labor market conditions influence the duration of beneficiaries in BF. Specifically, we analyze the impact of municipal employment changes on the likelihood of families exiting the program within the same locality.[1] Understanding household dynamics, including the individual or municipality-level factors that contribute to better incomes and the capacity of programs to respond to such changes, is critical for informing the sustainable design, operation, and support of CCTs.

Our identification strategy relies on combining panel data analysis with an instrumental variable (IV) approach. Gerard *et al.* (2021) show a positive effect of BF beneficiaries on formal employment at the local level in Brazil and attribute it to an economic multiplier effect. While those findings underscore the importance of accounting for local heterogeneity in the labor market we acknowledge the challenge of potential endogenous employment growth and reverse causality. We thus follow Bartik (1991) and instrument local employment growth with the national employment growth of over 600 industries and the share of the respective industry at the local level. The exogeneity of the instrument is given by the fact that national employ-

[1]Exits prompted by an increase in local employment may result from voluntary program exits or from official cross-checks revealing that families' per capita incomes exceed the eligibility threshold. In the case of voluntary exits, families can take advantage of the *retorno garantido* (guaranteed return), allowing them to re-enter the program within two years post-exit without being subject to a waiting list, provided they meet eligibility criteria.

ment growth across over 600 industries is plausibly uncorrelated with local economic shocks or unobserved local factors, affecting local employment growth only through the industry composition at the local level.[2] Our data – administrative data on BF beneficiaries as well as matched employer-employee data on formal employment – enables us to follow movements in and out of BF as well as formal dependent employment without interruption from 2012 up to 2019.[3]

Our primary results suggest that local employment growth leads to a small – yet statistically significant – increase in the probability of beneficiary families leaving the BF program. A 10% growth in local employment raises the exit probability by 0.342 percentage points, increasing the average transition rate of program exit from 8.61% to 8.69%. In addition, we find that these exogenous "rising tides" at the local level cause an increase in the probability of having at least one adult family member in a formal dependent job. Several robustness checks, such as replicating the analysis at the municipality level and checking for administrative capacities of the local authorities confirm our results.

Those findings indicate that the poor are responsive to local improvement in the labor market and confirm that a program can be operated in ways that are responsive to such income changes.[4] Nevertheless, the small size of the effects also highlights the relevance of policies that strengthen the capabilities and support of the poor to seize labor market opportunities.[5] Heterogeneity analysis of our results, in fact, shows that exits are concentrated among those households that are less likely to face labor force participation constraints, with fewer young children and more spare adult labor. This is consistent with the descriptive findings of another recent study on the family-level correlates of the BF benefit duration (Morgandi *et al.*, 2023).

The question is highly relevant for governments in many developing countries. After deploying CCTs on a large scale, often as a response to economic downturns, policymakers are now facing new challenges connected with their institutionalization. For programs to include new cohorts of young eligible beneficiaries, policymakers need to establish exit criteria that do not reverse the program's gains. The prevailing practice in high-income countries has been to link

[2]Using the leave-one-out estimator we calculate the national growth rate by excluding the local growth rate of the municipality we are calculating the instrument for. Thus, we rule out that the national growth rate is driven by the local growth rate. Given the large number of municipalities the scenario is unlikely, however, the strategy increases the credibility of our instrument.

[3]Our analysis stops in 2019 since re-certification requirements were suspended in 2020-2021 due to the COVID-19 pandemic.

[4]Exiting BF voluntarily enables the option of a guaranteed return to the program. If people exit through cross-checks they need to reapply to the program and might be subject to a waiting list. When individuals graduate from the program obtaining formal dependent employment they are eligible to other in-work benefits such as the family benefit *Salario Familiar*.

[5]Mourelo and Escudero (2017) show that active labor market policies integrated in cash transfer can increase the probability of having a formal job.

program exit to improvements in household income or living conditions. However, little has been researched on the income and labor market dynamics of CCT beneficiaries in developing countries.

Being among the few CCTs in developing countries that frequently reassess eligibility via household income tests, the BF program is ideal for exploring this question.[6] A rich set of administrative data on formal employment at the municipal level allows us to capture the relationship between "rising tides" in the local labor market and program exits, while individual data on job matches allows us to identify one of the likely channels for exits, the increase in formal employment of its beneficiaries.

In addition, the program itself has several optimal features to explore our research question. First, while much of the literature implicitly assumes that duration in CCTs programs is either exogenously determined by time limitation rules, or, absent these, largely indefinite, with families lasting in CCTs until children reach adulthood[7], the basic benefit of BF allows families and individuals to stay in the program as long as they meet the eligibility criteria of a per capita income below the eligibility threshold. In other words, not all families have to exit when children become adults. Second, the eligibility determination in BF depends on a centralized means test, instead of the more common proxy means test targeting. Families at the time of application self-report their income from all sources: this information then undergoes cross-verification with several other registries. The same verification process is repeated at each re-certification episode. As such, the program is sensitive to income fluctuations at entry and exit (Gazola Hellmann, 2015). These design features make BF an ideal case study on the factors that affect exit from CCTs, a question that, to the authors' knowledge, has not been studied before for CCTs or for programs in developing countries.

Our paper contributes to different strands of the literature. First, we add to the literature by examining the reasons that explain exits from social assistance. So far, the evidence originates mainly on programs in high-income countries.[8] Ayala and Rodríguez (2007) and Bäckman

[6] Beneficiaries are obliged to report any change in their income situation as soon as it happens. In addition, they need to update / re-verify their provided information every two years independent of changes.

[7] For instance a series of new studies estimates the long-term impacts of CCT programs on former beneficiaries who reached adulthood. Government efforts to deploy complementary interventions for families to increase chances of exit, or 'graduation', are also underpinned by similar assumptions about families' long-term stagnation in the programs (De Oliveira and Chagas, 2020; Fietz *et al.*, 2021).

[8] There are several explanations for this gap in the research. First, in a large share of CCT programs in developing countries, re-certification processes remain ad-hoc; second, programs adopting proxy means testing are more sensitive to changes in scores when household structural conditions change and less when incomes change, so fluctuations are few. Third, while beneficiaries in Brazil are well balanced between urban and rural areas, in many countries CCTs are mostly focusing on rural poverty, where formal income opportunities are rare. For all these reasons, several countries resort to making their programs time-bound or tied to beneficiary death or

and Bergmark (2011), for example, examined the impact of individual characteristics on the probability of exit in Spain and Sweden, finding that gender and prior work experience influenced exit probabilities. A recent policy note, on which the current research builds, looks at the duration of stay of families in BF more descriptively and identifies the level of education of adult members, labor supply constraints and prior work experience as significant predictors (Morgandi *et al.*, 2023).

Second, this paper also contributes indirectly to the vast literature on cash transfers and labor supply. Economic theory suggests that cash transfer may potentially reduce labor supply, especially in the formal sector, if the transfer generates a high marginal tax rate on labor earnings due to benefit withdrawal rules. In the case of BF, Fietz *et al.* (2021) show that from a theoretical *de jure* perspective, the program has an incentive-compatible design. The authors find that BF has one of the lowest personal and marginal tax rates on earned labor incomes when compared with other programs in the OECD.[9] Moreover, the BF program contains safeguards that allow beneficiaries to remain for additional time in the program when their income rises above the threshold at entry. Yet, it is unclear if families are entirely aware of these rules and act based on such incentives (Fietz *et al.*, 2021). For instance, Levy and Cruces (2021) argue that beneficiaries might prefer informal employment out of concern of not being able to re-enter the program if they leave.

The empirical evidence on work incentives and cash transfer programs generally indicates limited or no disincentive effects on labor supply.[10] For Brazil specifically, the evidence suggests that BF did not discourage (formal) labor market participation, although some studies find increases in informal hours worked.[11] Closely related to this is the research looking at labor

children reaching adulthood.

[9] Becker (1965) shows that individuals should increase their demand for leisure as non-labor income rises. Following this reasoning cash transfer recipients would be expected to reduce their labor supply as soon as they receive the monetary transfer. Additionally, beneficiaries might be influenced through various other channels – such as the health productivity effect, the self-employed liquidity effect, the insurance effect, and the investment in labor search effect (Baird *et al.*, 2018). Those effects, which may increase or decrease the labor supply of cash transfer beneficiaries, challenge the simplistic theory of the lazy welfare recipient.

[10] In a systematic review, Kabeer and Waddington (2015) finds negative effects on labor force participation in only one program (in Pakistan), though some studies document reduced formality (e.g., Garganta and Gasparini (2015)).

[11] Using the Brazilian household survey and exploiting a change in the program's eligibility line, Barbosa and Corseuil (2014) do not find evidence of BF distorting occupational choices toward informal jobs. Fruttero *et al.* (2020) use Brazilian data and an unannounced change in the program's eligibility rules. Restricting their sample to families that had just updated their information before the policy change was announced – hence, those families were unable to update information untruthfully due to the policy change – the authors find that BF beneficiaries are "4.7 percentage points more likely to be found at least once in a formal job in 2010 or 2011 and 3.3 percentage points more likely to be found in a formal job throughout these two years." The results are especially strong for younger cohorts (between 25 and 35 years old and 35 and 45 years old). De Brauw *et al.* (2015) find no overall impact on labor force participation of BF beneficiaries using longitudinal household-level panel data collected in 2005 and 2009. The authors, however, do find an increase in the intensive margin of informality (through

market constraints and childcare duties. Blundell *et al.* (2018), for example, show that childcare duties play an important role in labor supply decisions – especially for mothers.[12] Our research findings add to the existing literature by examining program exits and their relationship with local employment growth. We find that families exposed to "rising tides" in the labor market are not only more likely to exit BF but also more likely to have members transition into formal employment. This suggests that BF's design does not create strong disincentives against formal work participation even after being exposed to the program for some time.

The rest of the paper is structured as follows. Section 2 describes the institutional design of BF, its interaction with the rest of the tax benefit system and the data used. Section 3 presents some descriptive statistics followed by Section 4, where the methods used are explained. Section 5 shows results and robustness checks before we conclude in Section 6.

2 Institutional Design and Data

2.1 Bolsa Familia Program

Brazil was among the first countries in the world to embrace CCTs. Launched in 2003, BF aimed to alleviate both temporary and chronic poverty and fostered human capital development for children. When BF was first introduced, it also sought to consolidate several sub-national programs, such as *Bolsa Escola* and a gas subsidy (Lindert *et al.*, 2007; Bastagli, 2011; Fietz *et al.*, 2021). This section describes the rules and structure of BF as they applied in 2019. Since then, the program has undergone significant changes, including its replacement by *Auxílio Brasil* in 2021 and further modifications in 2023.

To receive assistance under the 2019 framework, families had to be registered in the single registry Cadastro Único (CadUnico).[13] BF consisted of two benefits: (i) the basic benefit and (ii) the variable benefit. As of 2019, the final year of our panel dataset, the monthly basic benefit was paid to families with a monthly per capita income of less than R$ 89 (USD 21.4). Families whose per capita income remained below R$ 89 (USD 21.4) also received a supplement so that the household would reach at least a monthly per capita income of R$ 89 (USD 21.4). The variable benefit was granted to individuals with a monthly per capita income below the

additional hours of informal work).

[12] Other references are Aguilar-Gomez *et al.* (2019) for Mexico, Berniell *et al.* (2021) for Chile, and Heath (2017) for theoretical evidence from Ghana.

[13] Individuals with a per capita income below 0.5 of the minimum wage (MW) were eligible to register in CadUnico. For more information about the registry, see Section 2.2.

poverty line (in 2019, R$ 178, USD 42.7), and the amount depended on the number of children or pregnant women in the family. In 2019, the program paid R$ 41 (USD 9.8) per month per child or pregnant woman, with a maximum of five variable benefits per family. The variable benefit was linked to education and health conditions (see Table 1 for an overview of the rules).

Table 1: Bolsa Familia rules as of 2019

Extreme poor families (monthly p.c. income below 89 R$/21.4 USD)	Poor families (monthly p.c. income below 178 R$/42.7 USD)
• Basic benefit (89 R$/21.4 USD per family) • Variable benefit (41 R$/9.8 USD per child or pregnant women, max. 5 variable benefits per family) • Top-up benefit after all other benefits (top-up to reach 89 R$/21.4 USD p.c. income)	• Variable benefit (41 R$/9.8 USD per child or pregnant women, max. 5 variable benefits per family)

Notes: The table describes the rules of Bolsa Familia as of 2019.

BF was not – and still is not – a constitutional right but a budgetary program, meaning that not everyone who was eligible for the program during our study period necessarily received it; the program had a waiting list. Each municipality registered vulnerable families and was allocated a budget based on poverty estimates from the Brazilian Institute of Statistics (Instituto Brasileiro de Geografia e Estatística – IBGE). The process of including new beneficiaries from the waiting list as spots became available followed a centralized procedure led by the Ministry of Social Development (MDS).

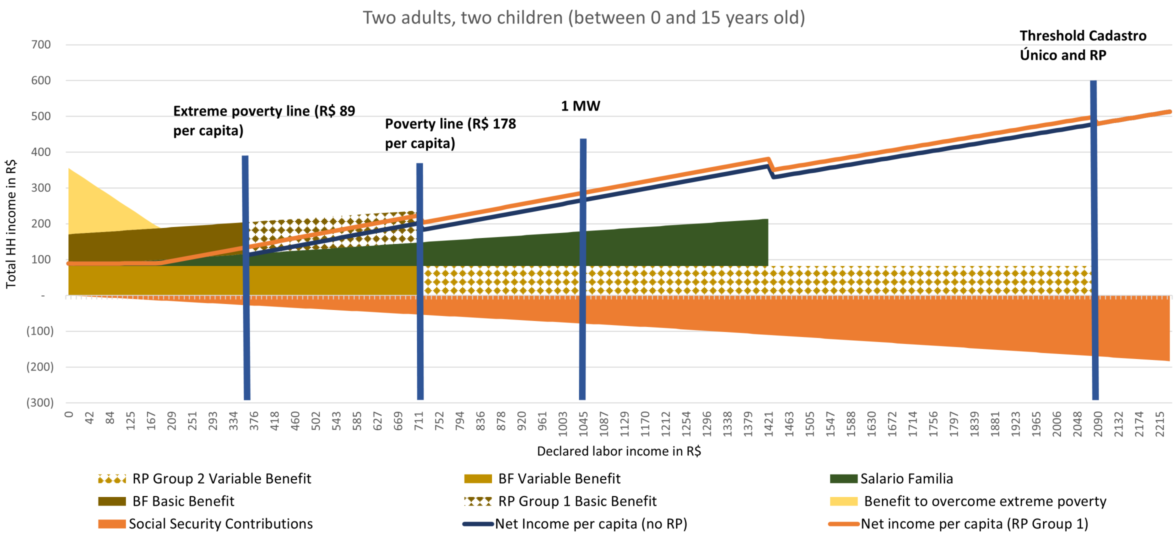
There were several reasons why families exited the program under the 2019 regulations and many of those still apply under the new program rules. The first related to changing household demographics: once children reached adulthood, families could only receive the basic benefit, and if their income exceeded the extreme poverty threshold, they were excluded from the program altogether. Second, if families failed to meet health and education conditions without sufficient justification, they were removed from the program after being offered opportunities to comply. Third, households were required to withdraw the cash benefit within a certain period; failure to do so resulted in exclusion from the program. Finally, household income had to remain below the eligibility threshold, though with one important exception: the *Regra de Permanencia* (permanence rule). This rule allowed beneficiaries to remain in the program for an additional two years and maintain their income above the eligibility line (up to certain limits), provided that they voluntarily reported their new income at a local social assistance office.

Administrative data showed that under the 2019 system, the vast majority of exits from BF occurred because families' per capita income rose above the eligibility threshold. The so-called *Averiguação e Revisão Cadastral* – inquiry and registration review – of existing beneficiaries cross-checked administrative records (such as those on formal employment) against beneficiaries' self-reported data in CadUnico. This process was carried out centrally in Brasília and operated independently of municipalities' economic conditions (Ministerio da Cidadania, 2013). BF beneficiaries were aware of the implications of taking up formal employment for eligibility, as it often led to either program exit or a transition into the permanence rule. Once family income exceeded the threshold, households were removed from the program. While some families left voluntarily, exclusion through the inquiry and registration review could also be considered voluntary since people aimed for higher income despite being aware of the consequences – namely, exclusion from the program (Ministerio da Cidadania, 2008).

BF's design and its interaction with the broader tax-benefit system created an incentive-compatible framework that should not have discouraged individuals from pursuing formal employment. The program had low marginal tax rates on acquired labor income compared to most social assistance programs (Fietz *et al.*, 2021). This was because the value of the BF benefit remained relatively low, fluctuating between a fourth and a fifth of the MW during the observation period. Additionally, Brazil extended automatic benefits to low-wage workers with children (*Salário Família*), which partially offset reductions in BF payments and social insurance contributions. Furthermore, personal income tax exemptions applied to workers at entry wage levels. Lastly, BF's permanence rule, *Regra de Permanencia*, acted as a temporary income disregard. Figure 1 visually illustrates the design of the BF program as it operated in 2019, including the implications of its permanence rule for a family in which an individual transitioned into full-time formal employment. Thus, even though eligibility was primarily determined by a family income test, nearly all family types experienced an increase in disposable income as wages rose, with minimal discontinuities. Given these factors, we hypothesize that beneficiaries might have favored formal employment over continued program participation if such an opportunity had arisen.

Since 2019, the BF program has undergone multiple changes. In 2021, it was replaced by *Auxílio Brasil*, which introduced modifications to benefit structures and eligibility rules. In 2023, BF was reinstated with further adjustments, including an increase in benefit levels. While the

Figure 1: Entering formal work and leaving BF



Notes: The model shows outcomes for a 4 people family, with 2 adults and 2 children between 0 and 15 years old. The family has 1 earner. The figure shows how benefits are withdrawn when entering formal employment. The BF basic benefit and BF variable benefit are granted based on mean testing and the number of children. The permanence rule (RP) allows beneficiaries to keep the benefits even if they see an increase in income (up to 0.5 MWs per capita) and update this information voluntarily at a local office. The value of benefits allowed to keep depends on the benefits received previous to seeing an income increase. If an individual lives in a family receiving only the BF basic benefit, she can keep the benefit under the permanence rule (RP Group 1). If an individual lives in a family that received both (the basic and the variable) benefit and sees an increase in income, she is allowed to keep the variable benefit (RP2).

core principles of conditional cash transfers remain, the specific rules changed.

2.2 Data

We rely on several administrative data sets which can be combined through anonymized identifiers.

CadUnico (Single Registry) The single registry is a national registry which was first established in 2001 in the context of Bolsa Escola (the predecessor of BF). It serves as a platform for all federal social programs in Brazil. Poor and vulnerable individuals who have a per capita income below 0.5 MWs can register themselves at the local social assistance office (*Centro de Referência de Assistência Social* – CRAS). The self-reported data contains socio-demographic and economic characteristics, such as age, gender, education, working status, income, and family composition. Individuals receiving social transfers must update their information at least every two years. In the case of a change of information, updates should occur immediately. The data extracted by the MDS refers to the middle of December each year. We can follow individuals over time by their *Número de Idenficação Social* (NIS), which is a unique registration number. The data covers 25,068,130 families (in 2012) living in 5,570 municipalities in the 27 states of the country.

Folha de Pagamentos do Bolsa Familia (BF payment records) The payroll dataset of BF contains information on the monthly payments received by every family. It does not allow for distinguishing between the different benefits but gives the total sum of transfers received. In addition, datasets on the exit reasons and people in the benefit graduation/transition rules (*Regra de Permanencia*) are available from 2016 onwards.

Relação Anual de Informações Sociais (RAIS) RAIS is an administrative dataset that contains information on formal dependent employment in Brazil. Every company needs to fill in the information on its employees' occupation, monthly compensation, contract type, date of entering the company, date of exiting the company, and dismissal reason. In addition, information on the firm, including the economic sector, the location, and the size of the establishment (defined by the number of employees), is available.

2.3 Sample Construction and Key Variables

We construct a panel to longitudinally track all individuals aged 18 to 59 who were newly registered in CadUnico and either belonged to a BF recipient family as of December 2012 or joined an already recipient BF family at some point during the observation period. BF participation is determined based on payment records, which are registered at the household head level. To identify all family recipients, we expand the payment information using the family identification number, ensuring coverage of all household members. Individual records in CadUnico are then matched to RAIS using the anonymized *Programa Integração Social* (PIS) number. The initial set of individuals is followed monthly until 2019. We then further collapse the data to a semester basis – enabling us to track individuals over 14 semesters and examine their transitions into and out of the formal labor market – and at the family level – to examine family-level movements in and out of the BF program. Figure A.1 in the Annex provides an overview of the data merging process.

Exiting Bolsa Familia Exiting BF is defined by using the program payment records (*folha de pagamento*). We define exiting BF as not being in the program for at least four consecutive months. This threshold has been chosen since beneficiaries who do not comply with program rules might get a grace period of three months in which the benefit is suspended, though people are not expelled from the program immediately. Additionally, we consider beneficiary families that enter the permanence rule as if they have left. The reasoning is that we want to identify the impact of employment changes at the municipality level on exit probabilities. The permanence rule, however, is a mechanism to delay, but not to prevent such exits. We only consider the first exit of a family since we do not want to estimate any effects on re-entry.[14] If the head leaves the social registry CadUnico, but a different person from the same family receives the benefits and thus *converts* to being the head, we classify this family as still *in BF*.

Formal labor market participation We identify formal labor market participation by merging information from CadUnico and RAIS. We classify families as having at least one member in formal dependent employment if any adult family member can be found in RAIS in a given semester.

Municipality-level employment growth We calculate employment growth at the municipality level using RAIS data. RAIS reports the number of job links, which slightly differs from the number of workers since a small share of individuals holds more than one formal job. To calculate the current stock of employment, we use job link data for the private sector, additionally excluding public firms within it, as hiring policies in the public sector are expected to follow different mechanisms. Employment growth is measured as the difference between the current period's number of private-sector employment links and the previous period's number of private-sector employment links, divided by the number of private-sector employment links in the previous period.

3 Descriptive Statistics

This section presents descriptive statistics of our sample. We start by laying out some characteristics of the individual data before describing some of the exit dynamics using the family data. In December 2012, the average age of individuals was 35. Individuals between 25 and 34 years old are the prevalent age group (32%), followed by individuals between 35 and 44 years old. In addition, 66% of individuals were female and 34% male, consistent with the targeting approach of the program (which privileges female household heads). The mean family size in 2012 was 3.6, and most families had one or two children. Most individuals are Afro descendent and have a middle school education (Annex Table A.1).

When registering in CadUnico, all adult members are also asked to report basic information regarding their employment status. Out of all individuals, 43% reported that they worked within the last 12 months. Most of them worked as self-employed, followed by formal dependent

[14] BF has a waiting list. Hence, not everyone eligible will get the benefits. These circumstances make estimation on entry difficult.

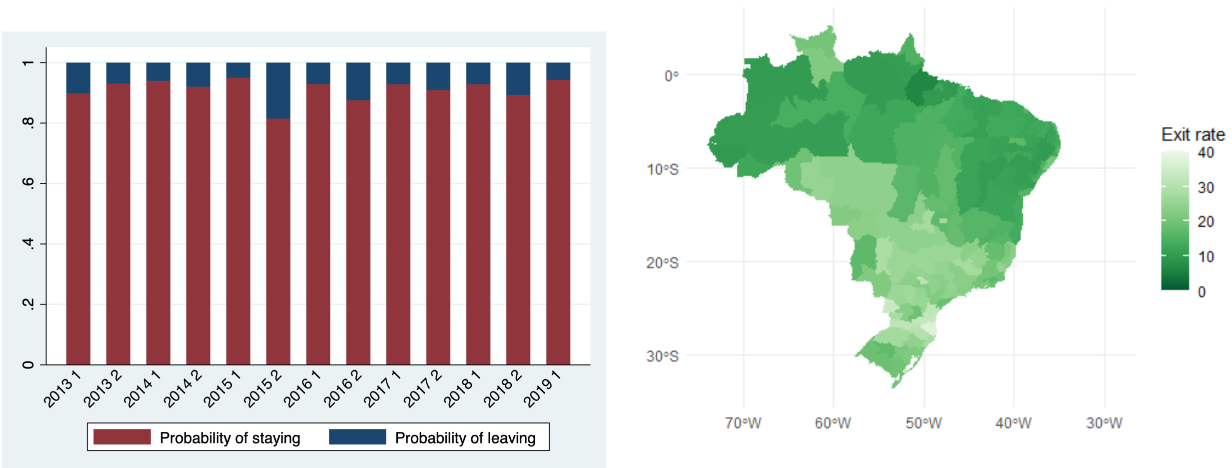
employment and temporary rural workers. The mean labor income in December 2012 for those that had positive labor income was R$ 290 (69.5 USD). We cross-check this information with RAIS and identify that 17% of all individuals (those that declared working or not within the last 12 months) had a formal job in December 2012 (more than the share declared in Cadastro), with a mean labor income of R$ 986 (236.5 USD) per month (Annex Table A.2).

Moving to the created family data, we see that around 70% of families leave at some point by the end of 2019. The average family stays in the program for 3.8 years (Table 2), and the transition probability out of the program ranges between 5% and 18% per year (8.61% on average) (Panel A of Figure 2). Exits from BF during our observation period were overwhelmingly permanent: only 14% of leavers rejoined the program by the end of 2019 (Table 2). However, we also know that the program suffered a waiting-list after 2015, and it is thus not possible to distinguish what share of BF graduates did not experience subsequent income shocks – which in general are estimated to be very frequent among the poor in Brazil (World Bank, 2021).

Figure 2: Transition probability and exit rates of Bolsa Familia

A. Transition probability of leaving BF

B. Exit rate of BF (Meso Region, 2nd sem. 2015)



Notes: Figure A shows the transition probability of leaving Bolsa Familia from one semester to the other. Figure B describes the average exit rate of Bolsa Familia beneficiaries by Meso Region in 2015, when exit rates peaked.

In addition, dynamism is also very heterogeneous on a geographic level (Panel B of Figure 2). The North and Northeast, traditionally poorer and with less formal employment, experienced much lower exit rates (between 0% and 10%) compared to the more developed and urbanized South and Southeast regions. The use of census-like national data also allows us to capture families as they move geographically. 7% of families moved to a different municipality during the observation period and 17% of those moved during the semester prior to exit (Table 2).

Finally, we explore with survival analysis the correlation between family and household head

Table 2: Family characteristics

	All families
Number of Families in BF	6,582,657
Number of Families that left during the observation period	4,602,881
Number of families that came back to the program	630,549
Number of families that moved to different municipalities	457,079
Number of families that moved to a different municipality prior to exit	80,629
Average number of years in the program	3.8
% of families having one member in formal dependent employment at entry	28.02
% of families having one member in formal dependent employment at exit	35.48
% of families having head in formal dependent employment at entry	15.12
% of families having head in formal dependent employment at exit	21.98

Notes: The table presents summary statistics for families registered in CadUnico in December 2012 for the first time and being in BF at the beginning of the first semester of 2013. Information on RAIS are obtained through a merge of CadUnico data, BF payroll information and administrative matched employer-employee data (RAIS).

characteristics of adults, as reported at the time of registration, and their probabilities to exit BF. This serves as useful descriptive evidence in support of the identification strategy for the effect of local employment changes on the probability of exit, which will be described in the next section. Following prior literature and Morgandi *et al.* (2023), we employ the Kaplan–Meier (KM) estimator and Cox regressions.[15] Table 3 shows that exit probabilities are correlated with some of the beneficiaries' observable characteristics at entry.[16] The speed and probability of exit from the program increase with age and education levels of the adults, particularly those with tertiary diplomas. Exit is also higher in urban areas. Families with 1 or 2 children have a higher probability of leaving the program while families having more than 3 children are less likely to leave compared to families without children.

4 Empirical Strategy

4.1 The Basic Model

To identify the effect of local employment growth on our two outcomes of interest – the probability of having at least one family member in formal dependent employment and on families'

[15]The KM estimator is a non-parametric statistic, which is used to estimate the survival function (in our case time in BF). The estimator can be written as $\widehat{S}(t) = \prod_{i:\ t_i \leq t} \left(1 - \frac{d_i}{n_i}\right)$, where t_i represents a time when at least one event (exit) happened, d_i the number of events (exits), which happened at time t_i, and n_i individuals known to have survived (have stayed in the program) up to time t_i. Cox regression is a method of investigating the effect of one or more variables upon an event takes to happen and can be written as $\lambda_0(t) = \lambda_0(t)e^{X\beta}$, where $\lambda_0(t)$ is a non-parametric baseline hazard function and X are matrices for the independent variables.

[16]A positive coefficient is associated with an increased likelihood of leaving the program. A hazard ratio (shown in column (2)) greater than 1 corresponds to a shorter time in the BF program, whereas a hazard ratio smaller than 1 indicates being for a longer time in the BF program.

Table 3: Cox regression results

	(1) Coefficient	(2) Hazard Ratio
Education head: Primary or less	0.0817***	1.085***
	(0.0020)	(0.0021)
Education head: Middle school	0.2490***	1.2828***
	(0.0019)	(0.0025)
Education head: Secondary school	0.3101***	1.3636***
	(0.0043)	(0.0059)
Education head: Tertiary	0.8949***	2.4472***
	(0.0136)	(0.0335)
Head 26 - 40 years old	0.2994***	1.3490***
	(0.0024)	(0.0032)
Head 41 - 50 years old	0.5134***	1.671***
	(0.0025)	(0.0042)
Head 51 - 69 years old	0.9329***	2.5419**
	(0.0027)	(0.0070)
Urban	0.3502***	1.4194***
	(0.0013)	(0.0018)
1 children	0.0695***	1.0720***
	(0.0019)	(0.0020)
2 children	0.0216***	1.0219***
	(0.0019)	(0.0020)
3 children	-0.0547***	0.9466***
	(0.0021)	(0.0020)
4+ children	-0.2064***	0.8134***
	(0.0024)	(0.0019)
N	4,456,917	4,456,917

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table shows Cox regression results. A positive coefficient is associated with an increased likelihood of leaving the program. A negative coefficient indicates a lower chance of leaving the program over time. A hazard ratio (shown in column (2)) greater than 1 corresponds to a shorter time in the BF program, whereas a hazard ratio smaller than 1 indicates being for a longer time in the BF program. Reference groups for education classifications and age groups are *illiterate* and *18-24 years old*, respectively.

propensity to leave BF – we employ panel data analysis with family-level and time-fixed effects. This approach allows us to control for unobserved time-invariant family characteristics that could be endogenous to our outcome variables. As it likely takes time for a local positive employment shock to translate into positive effects on the incomes of poor households, typically more detached from the labor market, and for the program to detect and react to any such changes, we estimate the effects on the outcomes of interest in the following period defined as one semester[17]:

$$Y_{i\tau t} = \beta_1 X_{it} + \beta_2 EmploymentGrowth_{\tau t-1} + \alpha_i + p_t + u_{it\tau}, \tag{1}$$

[17] While our data structure would allow to observe monthly movements, the time that it takes for the program to react is unlikely to be at a monthly level.

where $Y_{i\tau t}$ represents our outcomes of interest: A dummy variable which takes the value of 1 (i) if family i in municipality τ has a family member in formal dependent employment,[18] and (ii) our main outcome of interest: if a family i in municipality τ left BF.[19] Given the nature of the dependent variable, we use a linear probability model.[20] Employment Growth$_{\tau t-1}$ is defined as the change in the total number of formal private sector jobs in the municipality τ and semester $t-1$.[21,22,23] X_{it} is a vector of time-varying co-variates (age groups of the household head and the number of children living in a household).[24] α_i are family fixed effects that also capture in which trimester the family left, p_t are time-fixed effects. We use clustered standard errors at the municipality level since our treatment (employment growth) is happening at the municipality level.

4.2 Endogeneity Problem and Instrumental Variable Approach

To answer our research question we need to address several methodological challenges and potential sources of endogeneity.

Municipality-level population growth The first challenge is the identification of exogenous positive changes in local employment opportunities. While we can observe the total formal job growth by municipality per year/semester/month, we cannot control precisely for municipality-level population growth since the last census in Brazil was in 2010 (as of 2019). Yet, the population effect appears to be negligible (IBGE's annual estimates of population growth between 2011 and 2019 averaged 1% (IBGE, 2020)) compared to the role of local economic cycles. Formal employment has been closely following economic cycles, with a variation of about 12% between the lowest and highest levels in the same period. In fact, the Brazilian economy had more formal wage jobs in 2012 than in 2019 (MTE, 2019). In addition, large parts of the employed population in Brazil work informally (IBGE, 2019), so excess population growth, in the absence

[18] The dummy dependent variable *having a family member in formal dependent employment* takes the value of 1 if a family member is in formal dependent employment and 0 if no family member is in formal dependent employment.

[19] The dummy dependent variable (family i leaves BF) takes the value of 1 if the family leaves the program – based on the official payroll information of BF containing information on monthly benefit payouts of the benefit –, 0 if it stays, and is missing if the family is not in BF in the time-point.

[20] A conditional fixed-effect model could be used as well, but the linear probability model makes an IV approach and the interpretation of the results more straightforward.

[21] To obtain this information, we use RAIS data, which reports the number of job links, which slightly differs from the number of workers since a small share has more than one formal job.

[22] In the case that families moved between municipalities we consider the employment growth of the origin municipality as common in the migration literature (Jaeger *et al.*, 2018).

[23] In order to not have our results driven by extreme outliers, we winsorize employment growth at the 99.5 percentile. By doing so we change less than 1% of the municipalities' employment growth.

[24] The CadUnico data provides only a few variables that vary over time.

of formal dependent employment creation, tends to flow into unemployment, self-employment (often informal), or informality, which has been observed in Brazil during the last crises (Firpo and de Pieri, 2018; World Bank, 2020).

Multiplier effect caused by BF coverage The second methodological challenge relates to potential reverse causality, namely that the changes in coverage of BF cash transfers might affect levels of local employment through a local multipliers effect (Gerard *et al.*, 2021). At the national level, the number of beneficiary families remained more or less stable in our observation period (in December 2012, 13.9 million families were registered in BF compared to 13.2 million families in December 2019); however, we do observe variation at the local level, which might cause biases in our results (Ministerio da Cidadania, 2022).

Shift-share instrument For both challenges, we propose to use a shift-share instrument after Bartik (1991). In particular, we instrument local employment growth using national employment growth across more than 600 industries, interacted with the local share of each respective industry in the previous period. The instrument is plausibly exogenous, as national employment growth at the industry level is unlikely to be correlated with local economic shocks or unobserved local factors, affecting local employment growth only through the area's industry composition.

The Bartik instrument can be expressed as:

$$EmploymentGrowth_{\tau t} = \beta_0 + \beta_1 \sum_{\lambda} z_{\lambda \tau t-1} g_{\lambda t,-\tau}, \tag{2}$$

where $z_{\lambda \tau t-1}$ is the share of private sector employment in industry λ in municipality τ in $t-1$ and g_λ is the national growth rate of private sector employment in industry λ at time t.[25,26] We compile different variations of the shift-share instrument. We start by using annual growth rates. However, since we have monthly information on exits, we switch to semester growth rates. In an additional step, we exclude the growth rate of the municipality for which the industry is calculated. In other words, if we calculate the instrument for municipality τ in industry i, we exclude employment levels of industry i in municipality τ when computing the national growth rate (leave-one-out estimator, illustrated by $-\tau$ in model (2)). This gives additional credibility to the instrument since we can exclude concerns that national growth rates of a specific industry

[25] We follow the same procedure as above and winsorize the national employment growth by industry at the 99.5 percentile.

[26] We acknowledge that we could also work with initial shares at time t = 0, however, since we are looking at a long time period during which there were changing economic situations, looking at the shares of the previous semester seems more reasonable (Borusyak *et al.*, 2022).

are driven by the municipality for which the instrument is calculated. Excluding growth rates of the respective municipality is in line with Goldsmith-Pinkham *et al.* (2020) who state that the leave-one-out method addresses "the finite sample bias that comes from using own-observation information".

Our instrument also addresses any potential biases originating from the unobserved growth in informal labor income. The national labor demand shocks from formal industries cause changes in the local employment of formal industries which, in turn, might cause the BF beneficiaries to exit the program through some mechanisms. The most probable one is that the beneficiary herself gets a formal job. Informal labor income remains an unlikely reason for households to exit the program. Instead, formal jobs are more likely to be a cause for exit from BF – because such earnings are observable, and regularly cross-checked by authorities in Brazil. However, we also note that any other causes of informal sector growth which could correlate with the BF exits are offset by our IV approach.

While the relevance of the instrument can be observed from the data and will be discussed below, the validity of the instrument cannot be observed from the regression outputs. We are aware that there is a lively discussion in the literature on share (Goldsmith-Pinkham *et al.*, 2020) and shift (Borusyak *et al.*, 2022) exogeneity. In our case, we argue that national employment growth rates are independent of local employment shares – hence arguing for shift exogeneity. This is the case due to our calculation of the instrument (leaving-one-out method). The only way through which industry growth of a certain municipality would influence the national employment growth rate would be through a major shock in this given municipality, which would then, in turn, influence other municipalities, which would accordingly influence the national growth rate. This scenario is likely in cases with a small number of municipalities. However, due to our high number of industries (over 600) and municipalities (over 5,000), we argue that our shifts are exogenous.[27]

In addition, we acknowledge the fact that municipalities with similar industry structures might be subject to similar general trends as pointed out by Adao *et al.* (2019). While we follow the tests proposed by Borusyak *et al.* (2022) and Adao *et al.* (2019) in Section 5.2, we argue that even if similar industry structures are affected in similar ways, it is not necessarily worrisome in our setting. We are not trying to isolate a certain factor that affects employment but rather look at general employment trends. This is confirmed by Adao *et al.* (2019) who find that in their

[27] Shares might be endogenous since we have a frequent panel at the municipality level.

application the first stage differs less when looking at the application of Bartik (1991) since "the Bartik IV absorbs the bulk of the shift-share covariates that affect the change in the employment rate and wages across commuting zones." Section 5.2 shows further robustness checks to the instrument.

5 Results

5.1 Main Results

Formal labor market participation As a first step, we aim to understand if employment growth is directly impacting labor market participation of BF beneficiaries. Table 4 shows the results on formal labor market participation for the basic model and the IV approach in column (1) and (2) respectively. As can be seen, the basic model (column (1)) shows a small effect for our outcome of interest *labor market participation of at least one family member*. However, due to the above-mentioned endogeneity challenges, which mainly relate to reverse causality, we expect a downward bias for our results. This is confirmed by looking at the results using the IV approach. Column (2) of Table 4 indicates that employment growth causes a small and significant increase in the probability of having at least one family member in formal dependent employment. An increase of 10% employment growth at the local level increases the probability of having at least one family member in formal dependent employment by 0.259 percentage points. While the increase is small compared to the average formal labor market participation of 21.58%, is it not negligible compared to the average transition probability of 2.65%. The results suggest that employment growth is leading to a small – however statistically significant – increase in the probability of having a family member in formal dependent employment and thus motivates us to look at the impact of employment growth on exit dynamics.

Exit probabilities In the second step, we thus look at the impact of employment growth on the probability of leaving BF. Results of the basic model suggest the probability of exit changes significantly, however, to a small extent if employment at the municipality level increases (columns (1) and (2) of Table 5). As before, we interpret these results with caution, as potential endogeneity – particularly the risk of reverse causality – may bias the estimates downward. To address this concern, we turn to the IV approach (columns (3) and (4) of Table 5). The first-stage results confirm the relevance of the instrument, indicated by its statistical significance and a sufficiently high F-statistic. We find that the effect of employment growth is positive

Table 4: Formal labor market participation

	(1) In FLM Basic Model	(2) In FLM IV Approach
Employment Growth$_{t-1}$	0.0020** (0.0008)	0.0259** (0.0105)
Time-variant controls	✓	✓
Family-fixed effects	✓	✓
Time-fixed effects	✓	✓
F-Statistic		25.32
Mean FLMP	0.2158	0.2158
Average transition probability	0.0265	0.0265
N	52,020,809	51,354,456

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Notes: The table presents the main results from model (1) in column (1) and from the IV approach as specified in model (2) in column (2). The dependent variable is *a family has at least one member in formal dependent employment.* The regression controls for family- and time-fixed effects. Robust clustered standard errors at the municipality level are shown in parentheses.

and significant. Hence, an increase of 10% employment growth at the local level increases the probability that a family leaves BF by 0.342 percentage points (column (4) Table 5). The average employment growth in our study period was 2.4%, which then, in turn, caused an increase in the average transition probability by 0.08 percentage points: from 8.61% to 8.69%. It should be remembered that Brazil went through different economic cycles in our study period. While there were economic upturns, there were also economic downturns, which in part explain the small results.

Table 5: Exit probability

	(1) Exit BF Basic Model	(2) Exit BF Basic Model	(3) Exit BF IV Approach	(4) Exit BF IV Approach
Employment Growth$_{t-1}$	0.0036*** (0.0013)	0.0036*** (0.0013)	0.0334** (0.0148)	0.0342** (0.0151)
Time-variant controls		✓		✓
Family-fixed effects	✓	✓	✓	✓
Time-fixed effects	✓	✓	✓	✓
F-Statistic			25.34	25.32
Mean exit probability	0.0861	0.0861	0.0861	0.0861
N	52,319,618	52,020,809	51,655,314	51,354,456

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
Notes: The table presents the main results from model (1) in columns (1) and (2) and from the IV approach as specified in model (2) in columns (3) and (4). The dependent variable is *a family left BF*. The regression controls for family- and time-fixed effects. Robust clustered standard errors at the municipality level are shown in parentheses.

Those results can be understood as complementary to the results of Gerard *et al.* (2021). BF acts as both a social safety net and an economic stimulus that creates pathways to formal employment. The resulting labor market improvements facilitate beneficial exits that potentially free up resources for new beneficiaries.

5.2 Robustness Checks

Municipality level As a first robustness check, we replicated the analysis at the municipality level. Instead of using the individual probability of leaving the program, we here use *exit rates* as our outcome of interest.[28] Table A.3 shows that when replicating the analysis at the municipality level, we can see a similar effect compared to the individual level. Column (2) shows the outcome of the 2nd stage IV approach. If employment grows by 10%, the exit rate at the municipality increases by 0.245 percentage points.

Beneficiaries receiving the basic benefit As a second robustness check, we restrict our sample to those beneficiaries that receive either only the basic benefit or the basic and variable benefit (based on predictions derived from family composition and the total benefit amount). We thus exclude all families that *only* receive the variable benefit which is conditioned on having children. By doing so we are aiming to capture potential mechanical reasons – such as children approaching adulthood. The results shown in Panel A of Table A.4 are similar in significance level and magnitude as in our main specification.

Fraud In addition, we introduce a variable to identify individuals who secure formal dependent employment subsequently exiting the CadUnico, while their family remains enrolled. This approach is designed to address the possibility of individuals being incentivized to remove themselves from the registry once they secure formal employment, thereby enabling them to access both labor income and the BF benefit concurrently. Including such a variable does not change our point estimates, as shown in Panel B of Table A.4.

CadUnico actualization Further, we control for the share of CadUnico registries that have been updated.[29] We do so by including a variable that indicates the average value of updates by municipality. As seen in Panel C of Table A.4 including the actualization score does not alter the effect of employment growth on the probability of leaving BF.

[28]This approach allows us to also consider entries in the program. Thus, we calculate exit rates by looking at the number of exits per semester divided by the total number of families in BF.

[29]The MDS provides information on the actualization score (MDS, 2020).

Different instrument specification Next, we re-estimate our main specification by using a different shift-share instrument. Instead of using industries to calculate the instrument, we use 2,527 different occupations based on RAIS to calculate the national growth rates (shifters) and the local occupational shares. As in our main specification of the instrument, we exclude occupations related to the public sector as well as public firms. Results shown in Panel D of Table A.4 remain positive and significant and even have slightly higher point estimates. Nevertheless, in our main estimation strategy we prefer to follow Bartik (1991) to calculate the instrument and to use industries instead of occupations.

Validity shift-share instrument The recent literature has addressed the topic of the validity of shift-share instrument (see Goldsmith-Pinkham *et al.* (2020) and Borusyak *et al.* (2022)). As mentioned in Section 4 we follow the approach by Borusyak *et al.* (2022) to test our shift-share instrument for shock exogeneity.[30]

The authors suggest aggregating the data at the industry level to examine the conditional quasi-random shock assignment and the lack of correlation among shock residuals. Summary statistics for the shocks are presented in Table A.5. With a substantial number of shocks (8,579) and industries (660 at the 4-digit level and 278 at the 3-digit level), the statistics indicate that no single industry is significantly driving our observed effects. These findings demonstrate that we can mitigate concerns regarding the influence of any particular industry.

As a second step, we redo our analysis at the industry level as proposed by Borusyak *et al.* (2022). The authors show that the shift-share IV estimator equals the "second-stage coefficient from a s_n-weighted shock-level IV regression that uses the shocks g_n as the instrument":[31]

$$\bar{y}_{\lambda}^{\perp} = \alpha + \beta \bar{x}_{\lambda}^{\perp} + \bar{\epsilon}_{\lambda}^{\perp}, \tag{3}$$

where $\bar{y}_{\lambda}^{\perp}$ is the original (residualized) outcome (exit rate), and $\bar{x}_{\lambda}^{\perp}$ is the original (residualized) treatment (employment growth). As pointed out by the authors $\bar{y}_{\lambda}^{\perp}$ "reflects the average residualized outcome of the observations most exposed to the nth shock" and $\bar{x}_{\lambda}^{\perp}$ "is the same weighted average of residualized treatment". $\bar{x}_{\lambda}^{\perp}$ is instrumented by g_{λ}.

Borusyak *et al.* (2022) show that their exposure-robust standard errors are asymptotically equivalent to the ones proposed by Adao *et al.* (2019), who note that locations with similar

[30] While our main analysis is done at the family level, we do the robustness checks at the municipality level since our treatment is happening at the municipality level.

[31] In our case s_n equals s_{λ}.

industry structures might be subject to similar general trends. The equivalence is achieved by including exposure-weighted averages as controls in model (3).[32] Nevertheless, in our setting, similar industry structures which are affected in similar ways, are not necessarily worrisome as mentioned in Section 4.[33]

Column (1) in Table A.6 shows the results at the municipality level and using robust standard errors at the municipality level. Column (2) redoes the analysis at the industry level and uses robust standard errors at the exposure level. While our first stage F-Statistic stays significant, the significant level of our coefficient decreases; however, is still significant at the 10 % level. We acknowledge the fact that our coefficients differ slightly, however, we suspect that the difference arises due to the use of fixed effects in the panel data setting. Overall, we conclude that our instrument is still relevant at the industry level; however, the second-stage results have a lower significance level.

5.3 Heterogeneities

We next conduct heterogeneity analyses to examine how differences in municipal and individual characteristics shape families' exit dynamics in response to "rising tides".

Positive versus negative shifters First, we are interested in the question of whether the positive or negative shifters drive our results. Panel A of Table 6 shows the results of splitting the data in those families that live in a municipality that experienced on average positive employment growth and those that experienced on average negative employment growth. Results are driven by positive shifters, causing an increase in the probability of leaving BF. While those results display an interesting heterogeneity, they also increase the credibility of our main question – if employment growth (instead of decrease) causes an increase in the likelihood of leaving the program.

Informality Second, we aim to disentangle the effect for areas with historically high informality rates and areas with historically low informality rates. We classify municipalities by using the census data from 2010 into municipalities that have informality rates above and below

[32]The STATA command *ssaggregate* by Borusyak *et al.* (2022) is used. The command converts the shift-share IV dataset – in our case, at the municipality level – into a dataset of weighted shock-level aggregates. In other words, the outcome and treatment variables are regressed on exposure weights and a set of control variables to get to the industry-level aggregates.

[33]As outlined above we are not trying to isolate a specific factor that affects employment but rather look at general employment trends. This is confirmed by Adao *et al.* (2019), who find that in their application, the first stage differs less when looking at the application of Bartik (1991) since "the Bartik IV absorbs the bulk of the shift-share covariates that affect the change in the employment rate and wages across commuting zones."

Table 6: Heterogeneity by municipality characteristics

	Exit BF IV Approach
Panel A: Positive vs. negative employment growth	
On average neg. shifter	-0.0177
	(0.0258
F-Statistic	13.70
Mean exit probability	0.0792
N	36,151,808
On average pos. shifter	0.0598***
	(0.0221)
F-Statistic	87.63
Mean exit probability	0.1026
N	15,220,945
Panel B: Informality Level Municipality	
Above average informality	0.0821***
	(0.0254)
F-Statistic	15.43
Mean exit probability	0.0710
N	35,925,648
Below average informality	0.0603***
	(0.0225)
F-Statistic	12.47
Mean exit probability	0.1223
N	15,402,785
Time-variant controls	✓
Family-fixed effects	✓
Time-fixed effects	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents the results from the IV approach as specified in model (2). In Panel A municipalities are split into municipalities with on average positive and on average negative shifters. In Panel B municipalities are split into below- and above-average informality rates according to the Census of 2010. The regression controls for family- and time-fixed effects. Robust clustered standard errors at the municipality level are shown in parentheses.

the average. As shown in Panel B of Table 6 the effects are positive and significant for both types of municipalities. However, results show that the effects are stronger in municipalities with higher rates of informality indicating that in places, where formal dependent employment is less present, an extension of it causes a greater impact in terms of exits from the program.

Family composition Third, we split the sample into families that have just one adult living in the family vs. families with various adults. Panel A of Table 7 shows that the overall effect is driven by families with more than 1 adult. Those results seem plausible since single-headed households are commonly facing multiple constraints to benefit from formal employment growth

- such as childcare duties for example (Blundell *et al.*, 2018). In line with that, we see that families with smaller children – thus also having higher labor supply constraints – respond slightly less to employment growth than families with older children (Panel B of Table 7).

Education Last, we split our analysis based on distinct educational attainment levels. As shown in Panel C of Table 7, households headed by individuals with moderate education levels exhibit the most pronounced response to enhancements in local employment. Similarly, for families with heads having lower education, we find an increase in the likelihood of program departure when local employment improves. Conversely, households led by individuals with higher educational qualifications also see an increased probability of program exit; however, the effect is smaller and loses statistical significance. One plausible rationale behind this observation is that households headed by highly educated individuals already see an increased probability of departing from the program, as shown by the results obtained from prior survival analyses. Consequently, improvements in local employment might not be a necessary condition for those families to leave. Furthermore, these households might encounter supplementary constraints, as shown by the results in Panel A in Table 7.

6 Conclusion

CCTs have been a popular tool for poverty alleviation and human capital development. The impact of transfers on education and health outcomes has been the subject of several studies (Kabeer and Waddington, 2015; Millán *et al.*, 2019; Baird *et al.*, 2014). In contrast, graduation patterns of the transfers and the dynamics out of the programs remain vastly understudied. This paper contributes to the literature on cash transfers, CCTs in particular, by providing evidence on employment growth as an opportunity to graduate from social assistance programs. To the best of our knowledge, graduation from these kinds of programs has been highly neglected so far, possibly due to the lack of identified longitudinal data.

We start by analyzing the sociodemographic factors related to the program graduation and show that being male, being better educated, and living in urban areas are associated with a shorter time in BF. To isolate the effect of local employment growth on the probability of leaving BF, we combine several administratively identified datasets and follow families over a period of 84 months. By applying a shift-share IV approach and controlling for family- and time-fixed effects, we find that an increase in local employment has a positive and significant effect on leaving BF. Those results apply especially to families with less labor supply constraints. Several robustness checks – such as replicating the analysis at the municipality level, and looking at different specifications of the instrument – confirm our results. Additionally, our results show that employment growth increases the likelihood of having a family member in formal dependent employment, highlighting a potential pathway through which employment growth drives exits from the program. However, we acknowledge that we cannot capture all potential mechanisms – such as beneficiaries transitioning into self-employment.

One potential concern revolves around the classification of exits as *desirable*. Although our analysis reveals that only a small proportion of beneficiaries rejoins the program during the study period, it is crucial to interpret these findings cautiously, considering the presence of a waiting list during the period. The outcomes presented in this paper indicate that beneficiaries of the BF program experience positive outcomes from local employment growth, leading to their exit from the program. It underscores the importance of safety nets being designed with incentives that align with local economic dynamics. However, it is imperative that such safety nets exhibit sensitivity in both directions. While it is desirable for individuals to graduate from the program when their financial situation allows, the safety net should also be responsive in the event of families facing a loss in income. This highlights the need for a balanced and incentive-compatible design that accommodates both positive and negative shifts in beneficiaries' economic circumstances.

Our results indicate that the BF program, in its 2019 and prior design, effectively facilitated the graduation of beneficiaries during periods of economic upturn. However, to enhance the program's impact, specific public policies, such as employment training and childcare facilities, should be tailored to target the BF program. This targeted approach aims to maximize the opportunities for beneficiaries to capitalize on positive employment trends at the local level. Furthermore, ensuring the responsiveness of the safety net both – in and out of the program – is crucial for its overall effectiveness.

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Table 7: Heterogeneity by household characteristics

	Exit BF IV Approach
Panel A: Number of adults	
1 adult	-0.0041
	(0.0145)
F-Statistic	12.95
Mean exit probability	0.0778
N	20,705,743
1+ adult	0.0583***
	(0.0181)
F-Statistic	33.73
Mean exit probability	0.0908
N	30,276,708
Panel B: Number of children	
Children below 6 years old	0.0327**
	(0.0144)
F-Statistic	26.23
Mean exit probability	0.0737
N	22,668,011
Children 6 - 12 years old	0.0399***
	(0.0153)
F-Statistic	29.69
Mean exit probability	0.0788
N	26,718,895
Children above 12 years old	0.0389**
	(0.0159)
F-Statistic	32.30
Mean exit probability	0.0914
N	23,228,427
Panel C: Education Level Household Head	
Low education	0.0403**
	(0.0164)
F-Statistic	13.97
Mean exit probability	0.0715
N	11,546,832
Middle education	0.0472***
	(0.0147)
F-Statistic	35.43
Mean exit probability	0.0828
N	22,947,471
Higher education	0.0291*
	(0.0177)
F-Statistic	22.82
Mean exit probability	0.0986
N	16,661,116
Time-variant controls	✓
Family-fixed effects	✓
Time-fixed effects	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

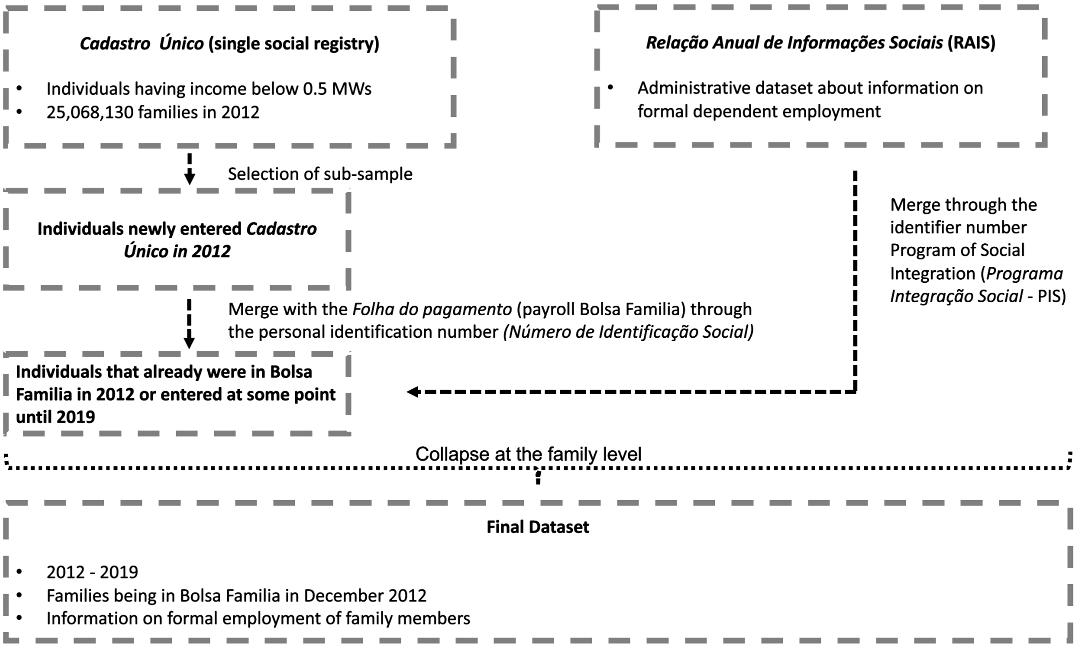
Notes: The table presents the results from the IV approach as specified in model (2). In Panel A the sample is split into 1 adult families vs. more than 1 adult in families. In Panel B the sample is split into families having small children (younger than 6 years old), families having children between 6 and 12 years, and families having older children (older than 12). In Panel C the sample is split into families having a head of low education (basic school education or less), a head of middle education

Appendix

Additional Figures

Additional Tables

Figure A.1: Data merging process



Notes: The Figure illustrates the data merging process describes in Section 2.3.

Table A.1: Socio demographic characteristics

Mean family size	3.6
Age	
Mean age all	34.7
Mean age 1 person HH	41
18-24	0.22
25-34	0.32
35-44	0.26
45-54	0.17
55-59	0.03
Gender	
Female	0.66
Male	0.34
Children	
No children	0.22
1 child	0.32
2 children	0.26
3 children	0.12
4+ children	0.07
Race	
Black	0.09
Indigenous	0.01
Mixed Race	0.65
Asian	0.00
White	0.25
Schooling Level	
Illiterate	0.12
Primary or less	0.31
Middle School	0.49
Secondary	0.08
Tertiary	0.00
Urban / Rural	
Urban	0.74
Rural	0.26
Region	
North	0.11
Northeast	0.51
Central-West	0.06
Southeast	0.25
South	0.08

Notes: The table describes socio-demographic characteristics of our study sample at the individual level in 2012.

Table A.2: Working characteristics

Worked within the last 12 months (CadUnico)	
No	0.57
Yes	0.43
Work type (CadUnico)	
Apprentice	0.00
Employer	0.00
Formal (dependent)	0.19
Formal domestic	0.01
Government / Military	0.01
Informal (dependent)	0.07
Informal domestic	0.03
Self-employed (formal & informal)	0.48
Temporary rural	0.18
Unpaid labor	0.03
Income in R$ (CadUnico)	
Mean labor income	290
In formal employment (RAIS)	
Yes	0.17
Income in R$ (RAIS)	
Mean labor income	986

Notes: The table describes labor market characteristics of our study sample at the individual level in 2012.

Table A.3: Robustness: municipality level

	(1) Exit rates Basic Model	(2) Exit rates IV Approach
Employment Growth$_{t-1}$	0.0060***	0.0242***
	(0.0011)	(0.0066)
Municipality fixed-effects	✓	✓
Time fixed-effects	✓	✓
F-statistics 1st stage		250.65
Mean exit rate		0.1391
N	72,254	72,254

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents the results from the IV approach as specified in model (2), however, doing the analysis at the municipality level. The dependent variable is *exit rates* of BF beneficiaries. Robust standard errors are shown in parentheses.

Table A.4: Robustness

	(1) Exit of BF IV Approach
Panel A: Beneficiaries receiving the basic benefit	
Employment Growth$_{t-1}$	0.0329**
	(0.0157)
F-statistics 1st stage	20.79
Mean exit probability	0.0861
N	44,648,615
Panel B: Controlling for being in formal dependent employment and leaving CadUnico	
Employment Growth$_{t-1}$	0.0341**
	(0.0151)
F-statistics 1st stage	25.32
Mean exit probability	0.0861
N	51,354,456
Panel C: Controlling for CadUnico actualization score	
Employment Growth$_{t-1}$	0.0344**
	(0.0151)
F-statistics 1st stage	25.28
Mean exit probability	0.0861
N	51,354,456
Panel D: Occupational instrument	
Employment Growth$_{t-1}$	0.0436***
	(0.0094)
F-statistics 1st stage	114.85
Mean exit probability	0.0861
N	51,353,601
Time-variant controls	✓
Family fixed-effects	✓
Time fixed-effects	✓

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table presents the results from the IV approach as specified in model (2). Panel A restricts the sample to those families receiving at least the basic benefit. Panel B controls for an additional variable indicating if a family member disappeared from the family registry in CadUnico after obtaining a formal dependent job. This approach aims to control for fraud in the program. Panel C controls for an additional variable indicating the actualization score of CadUnico. Panel D uses occupational codes instead of sector codes to calculate the IV. Thus, $z_{\lambda\tau t-1}$ is the share of private sector employment in occupation λ in municipality τ in $t-1$ and g_λ is the national growth rate of private sector employment in occupation λ at time t. Robust clustered standard errors at the municipality level are shown in parentheses.

Table A.5: Shock summary statistics

	(1)	(2)
Mean	0.004	0.000
Standard deviation	0.258	0.258
Interquartile range	0.044	0.048
Specification		
Residualizing on period FE		✓
Effective sample size (1/HHI of s_{nt} weights)		
Across 4-digit industries and periods	726.907	967.919
Across 3-digit industries and periods	33.69	33.69
Largest s_{nt} weight		
Largest emp. share	0.006	0.006
Largest emp. share 3 digit	0.092	0.092
Observation Counts		
# shocks	8,579	8,579
# industries	660	660
# 3 Digit groups	278	278

Notes: The table follows Borusyak *et al.* (2022) and summarizes the distribution of employment shows shocks across industries and time periods. Shocks are measured as the national growth rate of a certain industry. Column (2) residualizes shocks on period indicators. The Table also reports the effective sample size (the inverse renormalized Herfindahl index) across 4- and 3. digit industries and periods.

Table A.6: Industry level regression

	(1) Exit rate BF Municipality level	(2) Exit rate BF Industry level
Employment Growth$_{t-1}$	0.0242***	0.0245*
	(0.0066)	(0.0137)
Municipality / Industry fixed-effects	✓	✓
Time fixed-effects	✓	✓
Industry shares		✓
F-statistic	250.65	40.60
Number of region-periods	72,254	72,254
Number of industry-periods	8,579	8,579

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table follows Borusyak *et al.* (2022) and redoes the analysis at the industry level. Column (1) shows the specification at the municipality level with robust clustered standard errors at the municipality level as shown in Table A.3. The specification controls for time and municipality fixed-effects. Column (2) shows the results of the analysis at the industry level and including exposure-robust standard errors. The first-stage F-statistics are obtained from equivalent industry-level IV regressions as indicated by Borusyak *et al.* (2022). The specification controls for industry shares and time- and industry-fixed effects.