Do CCTs Create Conditions to Thrive? *Bolsa Família* and Social Mobility in Brazil*

Diogo G. C. Britto† Alexandre Fonseca‡ Paolo Pinotti§

Breno Sampaio¶ Lucas Warwar‖

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Abstract

Conditional Cash Transfers (CCTs) are widely used as poverty-reduction policies, yet their long-term effects on socio-economic outcomes remain uncertain. This paper fills this gap by examining the intergenerational effects of the largest CCT in the world, Brazil's Programa Bolsa Família (PBF). Employing a differences-in-differences design and a comprehensive dataset covering cohorts born between 1970–1994, we find that PBF significantly promotes human capital accumulation, leading to reduced dependency on the social safety net, higher earnings, and intergenerational income mobility among the next generation. These effects are more pronounced for younger children and females, highlighting the importance of early exposure to the program and its role as a driver of greater equality. Our findings underscore the effectiveness of CCTs in breaking the intergenerational cycle of poverty and fostering social mobility, with valuable implications for policymakers worldwide.

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†Bocconi University, CEPR, and BAFFI-CAREFIN Center, CLEAN Unit for the Economic Analysis of Crime, GAPPE/UFPE, IZA, e-mail: diogo.britto@unibocconi.it.

‡Federal Revenue of Brazil, GAPPE/UFPE, e-mail: alexandre.fonseca@rfb.gov.br

§Bocconi University, CEPR, CESifo, CReAM, and BAFFI-CAREFIN Center, CLEAN Unit for the Economic Analysis of Crime, CEPR, e-mail: paolo.pinotti@unibocconi.it

¶Universidade Federal de Pernambuco, GAPPE/UFPE, IZA, e-mail: breno.sampaio@ufpe.br.

‖Stanford University, GAPPE/UFPE, e-mail: warwar@stanford.edu.

1 Introduction

Conditional Cash Transfers (CCTs) are the backbone of poverty-reduction policies in many countries, particularly in the developing world (World Bank, 2018). By design, CCTs have two main goals. In the short-term, cash transfers to poor households aim to ease financial constraints and alleviate poverty immediately. By conditioning such transfers to children's education and health checks, CCTs' long-term purpose is to enable sustained social mobility, i.e., break the intergenerational cycle of poverty. While several studies document that CCTs are effective in the short-term (Fiszbein et al., 2009; Bastagli et al., 2016), whether short- and medium-term effects on poor children translate into better living conditions in adulthood remains an open question (Molina Millán et al., 2019; Garcia and Saavedra, 2023).

In this paper, we estimate the long-term effects of the largest CCT program in the world, Brazil's *Programa Bolsa Família* (PBF). Created in 2004, PBF is the main welfare program in the country, assisting over 14 million households as of 2019. Many studies show that PBF had positive short-term impacts on poor children's education and health outcomes (Viana et al., 2018). Still, the main purpose of the program was to offer conditions for these kids to move away from economic hardship in adulthood. Thus, we combine different administrative datasets tracking adult outcomes for over 20 million people born between 1970–1994 to ask whether individuals exposed to PBF during childhood display improved socio-economic conditions later on. Such large-scale assessment of long-term impacts is still rare in the literature and key for policy-making in both developing and developed countries (Blattman et al., 2017; Gentilini et al., 2020).

Similar to other analyses of intergenerational effects of the social safety net (Goodman-Bacon, 2021; Bailey et al., 2023), we employ a differences-in-differences design in which temporal variation comes from cohorts born earlier versus later relative to PBF implementation. We flexibly assess PBF's effects by age at implementation with event studies in which control cohorts have adult outcomes effectively determined when the program began (ages 25–34 in 2004). Using mother fixed effects, we compare children young enough to benefit from PBF with their older siblings in families with low versus high exposure to the program. In particular, we measure exposure using a Machine Learning (ML) model that identifies households' likelihood to participate in the program given pre-determined characteristics.[1] Finally, to account for convergence between regions and the expansion of Brazil's welfare state in the period, all baseline regressions include city-by-cohort fixed effects and directly control for children's exposure to the roll-out of social programs contemporary to PBF.

Our main result is that PBF promoted human capital accumulation for its beneficiaries,

[1] This approach is akin to Cengiz et al. (2022), in which the authors train an ML model to identify workers more likely to be exposed to a minimum wage increase.

leading to intergenerational income mobility among the next generation. We first document that boys and girls exposed to the program's conditionalities between 10–15 years old attain 1.3 and 1.9 more years of education, respectively – implying gains of 14% and 19% relative to their baseline counterfactuals.[2] This higher educational attainment is reflected in better chances of completing high school – around 9 p.p. (15%) for boys and 12 p.p. (21%) for girls – but remarkably in a substantial increase in the probability of obtaining a college degree, which more than doubles for both genders. Notably, we also find small gains in attainment – around 0.5 years, or less than 5% – for young adults aged 16–21 at the start of the program. However, such gains are fully concentrated on higher high school completion rates, with no improvements in the obtainment of a college degree.

These heterogeneous effects across cohorts are likely related to PBF's design, as only children who are 15 years or younger are directly impacted by the program's conditionalities.[3] Indirect effects on older children (16–21) may arise from the relatively large household-level income shock promoted by the cash transfer – which potentially reduces the opportunity cost of young adults remaining in school but is unlikely to foster meaningful changes in skill development (Heckman and Mosso, 2014).[4] In turn, the more significant effects on young children are probably linked to a lengthened exposure to PBF's conditionalities from an earlier age, which can improve conditions related to human capital acquisition.

In line with this notion, we next show that PBF is also related to higher chances of working in the formal labor market – but increased labor supply is associated with higher earnings only for children impacted by the program's conditionalities. In particular, boys and girls aged 10–15 at the start of the program are, respectively, 8 p.p. (14%) and 14 p.p. (40%) more likely to hold at least one formal job between 23–25 years old, while the effect for their older siblings is around 5 p.p. (8–14%). In turn, effects on earnings only emerge for younger children and amount to around 2,300 BRL/year (30%) for males and 1,450 BRL/year (40%) for females. Consistent with higher earnings, children who grew up in families which received PBF transfers are 4 p.p. less likely to participate in the program as adults, or a 30% drop relative to their baseline counterfactual. This result is an important indication that PBF promoted social mobility and contradicts the common-held argument

[2]In line with the differences-in-differences design, we compute counterfactuals for exposed children's outcomes by adjusting the baseline of non-exposed cohorts in the treated group by the relative change across cohorts in the control group.

[3]This is particularly true in our setting, which analyses effects on children impacted in the first years of the program. In 2008, a slight reform introduced conditionalities for children aged 16–17 years old, but children in our sample potentially affected by it were already younger than 15 in 2004.

[4]Despite high school completion in Brazil is expected at 18 years old, significant levels of grade distortion – especially among the poor – can help explain the effects on young adults in their early 20s. Moreover, the possibility of seeking supplementary education later in life also explains part of the observed effects.

against CCTs that its beneficiaries become "dependent" or "lazy" in the long-term.

Nevertheless, even with higher earnings and lower dependency on social programs, beneficiary children could still grow up to be at the bottom of the income distribution. To assess this, we replicate the methodology in Britto et al. (2022a) to account for informal income and construct cohort- and gender-specific income distributions. We then show that PBF is associated with intergenerational income mobility, but again only for children directly impacted by its conditionalities. Boys and girls exposed to the program rank, respectively, 6.3 and 4.3 percentiles higher in their respective income distributions – corresponding to relative gains of nearly 15%. Besides impacting mean income ranks, PBF also affects probabilities of being in the tails of the income distribution. For instance, boys and girls are, respectively, 10.4 p.p. (15%) and 14 p.p. (23%) more likely to be outside the poorest 20% and 5.8 p.p. (69%) and 5.2 p.p. (87%) more likely to be among the richest 20%. This set of results underscores that PBF promoted both the exit from poverty and extreme upward mobility, succeeding in its long-term goal of enabling sustained social mobility.

Furthermore, we show that PBF is related to significant reductions in migration rates across cohorts, which relates to anecdotal and empirical evidence of welfare programs lessening the need for "desperate moves" among the extremely poor in Brazil. We also find that girls exposed to the program early on observe significant decreases in teenage pregnancy rates – around 2 p.p., or 20% – which may point to an important mechanism behind social mobility, as teenage pregnancy is pervasive among vulnerable households in Brazil and has lasting consequences for girls. Finally, PBF marginally improves survival rates for children and young adults exposed to the program, which is potentially linked to better health outcomes overall and reduced engagement in risky behavior.

Across all outcomes, we find that relative effects are consistently larger for girls. In additional heterogeneity analysis, we also document that relative effects are larger for nonwhites and children growing up in the North/Northeast regions of the country. Since these groups are relatively more disadvantaged, this goes in hand with the focused approach of PBF, which aims at targeting the most vulnerable groups in society. Likewise, PBF can be (cautiously) interpreted as reducing racial and regional disparities in income mobility, which speaks to broad evidence that the program contributed to the reduction in income inequality in Brazil between 2000–2010 (Souza et al., 2019). Moreover, we show that PBF effects are higher in places with above-median quality of the public educational system and for children whose mothers are relatively more educated – suggesting that both place and family inputs are relevant to the effectiveness of the program. This suggests that the availability of opportunities in a given place mediates CCTs' capability to promote children's social mobility and that it does not replace important family inputs in the process of child development.

In sum, we document that PBF impacted a wide range of long-term outcomes. While the household-level income shock promoted by cash transfers was able to increase high school completion rates and formal labor supply of young adults in exposed families, younger children directly impacted by the program's conditionalities also observed lasting improvements in earnings and income mobility. This set of results is an important empirical support for CCTs' design, showing that conditionalities can be remarkably successful in achieving the long-term goal of breaking the intergenerational cycle of poverty, while immediate cash transfers can have positive indirect effects on other members of the household. To the best of our knowledge, this paper conducts the first robust in-depth empirical analysis of the intergenerational impact of a CCT program – and does so in the context of the largest CCT in the world, PBF. Our work makes contributions to three strains of the literature.

First, to the wide set of studies on the impacts of CCTs reviewed by Fiszbein et al. (2009); Bastagli et al. (2016); Molina Millán et al. (2019); Garcia and Saavedra (2023). In particular, we add robust evidence to a growing literature showing that CCTs promote sustained education gains for poor children (Barham et al., 2018; Molina Millán et al., 2020; Araujo and Macours, 2021; Barrera-Osorio et al., 2019; Cahyadi et al., 2020; Attanasio et al., 2021), deepening the analysis on a longer time horizon and across more outcomes. In this regard, the most similar paper to ours is Parker and Vogl (2021) long-term follow-up of Mexico's *Progresa*, which has a more limited scope.[5] Importantly, we are the first to combine an analysis of CCTs and carefully computed intergenerational mobility measures, which is crucial to evaluate the long-term performance of such programs relative to their goals.

Furthermore, our results relate to the rich literature on child development documenting that skill formation is an intricate process that impacts several life outcomes (Heckman and Mosso, 2014). In particular, our results dovetail nicely with the finding that investing in skill formation in disadvantaged children turns them more productive in the future. In the context of PBF, we show that this leads to upward social mobility. Finally, we also speak to studies analyzing the intergenerational effects of the social safety net, which have focused on the U.S. context (Bailey et al., 2023; Barr et al., 2022; Goodman-Bacon, 2021).

The paper is structured as follows: Section 2 gives details on PBF's institutional background and the expected long-term effects of the program. In Section 3, we introduce the data and describe our empirical strategy. Our main results of PBF effects on adult outcomes are discussed in Section 4. Finally, Section 5 concludes.

[5] In particular, the use of a municipal-levelæ variation on Census data with high attrition rates complicates Parker and Vogl (2021) identification, which also relies on smaller samples and fewer outcomes.

2 Institutional Background

2.1 The Programa Bolsa Família (PBF)

Created in 2004, PBF is the largest CCT program in the world. As of 2019, it reached 15 million families – roughly 30% of the population – with an average stipend of 180 BRL per family, costing 0.5% of the GDP annually. It is broadly considered a successful program among policy-makers, and contributed to the spread of CCTs around the developing world.

Under PBF, every family with per capita income below a national poverty threshold is eligible for a variable benefit that depends on the number and age of the children. As of 2019, this threshold was 140 BRL and families could accumulate up to five children (0–15 years old) and two youth (16–17 years old) monthly benefits of 32 and 38 BRL each, respectively.[6] Transfers are conditional on children's school attendance and vaccination. In addition to the variable benefit, families with per capita income less than half of the poverty threshold receive an unconditional monthly benefit of 70 BRL. Eligible households can self-enroll at a social assistance center or be prospected to the program by a social assistance team. Transfers are preferentially entitled to the mother of the household and conditionalities are enforced jointly by municipalities and the federal government.

2.2 PBF in the Short-run and Expected Long-term Effects

The design of CCTs relies on some key assumptions (Garcia and Saavedra, 2023). Foremost is that enhancing poor children's human capital will lead to improved socioeconomic well-being in adulthood. This is related to a rich literature showing that cognitive and non-cognitive skills developed during childhood are highly associated with a wide range of adult outcomes (Heckman and Mosso, 2014). Moreover, CCTs consider that human capital accumulation is a function of time spent in school and, importantly, these programs believe that they improve human capital acquisition by helping households overcome demand-side constraints such as educational externalities, informational constraints, and opportunity costs of children's time.

A large literature seems to indicate that PBF is successful in lessening such constraints, improving children's school enrollment and attendance rates in the short-run (Viana et al., 2018). Furthermore, these studies underscore that PBF also improves children's health outcomes and overall household conditions, which could also benefit the process of human capital acquisition. Therefore, we aim to test whether the alleviation of constraints indeed leads to higher human capital and improved adult outcomes for exposed children, especially on earnings and social mobility – which would largely support the program's design.

[6] At implementation, families could only receive up to two child benefits. The youth benefit and the higher child limit were implemented in 2008. Monetary values of transfers and the poverty threshold are regularly adjusted for inflation.

3 Data and Methodology

3.1 Data

We combine several administrative records to perform our analysis. Our sample of children is the Brazilian person registry (*Cadastro de Pessoa Física*, CPF), which covers the entire population and is provided by the Brazilian tax authority. All individuals are identified by their person code, full name, and mother's full name. We restrict the sample to children born between 1970 and 1994 (aged 10 to 34 years old when PBF started) and whose mothers are uniquely identified by their names.[7] In this way, we can link them to their mothers' and retrieve their characteristics before the launch of PBF. Our final sample comprises over 23 million children, around half of the cohorts studied.

We track individuals' participation in PBF using administrative records on the program's payments from 2004 to 2020. We observe children's educational and labor market outcomes from administrative employment data covering the population of formal jobs for the 2002-2019 period (*Relação Anual de Informações Sociais*, RAIS) and entrepreneurship activity via the Brazilian firm registry (CNPJ). We observe fertility, migration, and location decisions from updates in CPF. Finally, we follow the same methodology in Britto et al. (2022a) to measure individual-level informal income and compute social mobility measures.[8]

3.2 Empirical Strategy

We expect PBF's long-term effects to be higher for children impacted at younger ages, while young adults impacted by the program after adult outcomes are determined could not be affected by it, by definition. Accordingly, we use a differences-in-differences setup in which temporal variation comes from cohorts born earlier versus later relative to PBF implementation. We measure family-level exposure to PBF and compare children young enough to benefit from the program with their older siblings (first difference) in families with low versus high probability of being targeted by the program (second difference).

We identify families' exposure to PBF by predicting their likelihood to participate in the program in 2004 using a Machine Learning (ML) algorithm, akin to Cengiz et al. (2022). The baseline model uses mothers' education, age, number and age of their children, formal employment background, and city of residence as features.[9] Table 1 shows mothers' characteristics by deciles of their predicted "PBF score", showing that highly-exposed mothers

[7] Due to accumulation of surnames, around 52% of Brazilians have a unique name. In Britto et al. (2022b), it is shown that the uniquely-named population is representative of the overall population.

[8] A detailed description of the variables used as outcomes in the following sections can be found in Appendix Table A.1.

[9] All covariates are measured before the start of PBF. We use data only for the first year of the program to avoid endogeneity concerns about selection into the program and its roll-out.

are concentrated in the North and Northeastern regions of the country, have more children, and lower educational levels. In our baseline specification, the treatment group comprises children whose mothers are at the top 25% of the predicted-probabilities distribution – in line with participation rates as shown in Table 1.

Table 1: Mother's characteristics by deciles of predicted PBF score.

Decile	Age (2004)	High School	Formal Income	Lives in N/NE	Age 1[st] childbirth	No. of kids	PBF transfers 2004-08 (BRL/y)	Children's PBF eleg.	PBF score
1	50.81	0.98	35754.06	0.07	26.52	1.93	0.31	0.00	0.00
2	50.02	0.85	7894.13	0.07	24.82	2.13	1.31	0.00	0.00
3	47.27	0.76	4163.67	0.13	24.48	2.20	3.09	0.01	0.01
4	45.29	0.64	3619.99	0.15	23.99	2.33	6.88	0.04	0.01
5	44.77	0.50	2897.17	0.19	23.57	2.43	15.08	0.09	0.02
6	44.32	0.42	2352.48	0.22	23.05	2.57	31.58	0.19	0.03
7	41.96	0.39	1636.16	0.27	22.61	2.55	63.21	0.48	0.06
8	39.73	0.28	1071.93	0.32	22.10	2.67	127.67	1.12	0.12
9	38.08	0.12	535.00	0.35	21.74	2.84	241.26	2.21	0.21
10	37.11	0.05	232.94	0.61	20.80	3.69	478.79	3.63	0.38

Notes: The table reports mothers' characteristics according to deciles of their predicted probability of participating in PBF, as computed by the ML model. In our baseline specification, the treatment group includes children whose mothers are in the top 25% of the predicted-probabilities distribution.

We estimate reduced-form event-study specifications to validate the research design and flexibly assess PBF's dynamic effects relative to age at the start of the program:

$$y_{iamt} = \sum_{t=10}^{34} (\boldsymbol{I}_t \times Treat_a)\,\mu_t \;+\; Treat_a \mathbb{X}'_{mt}\Omega \;+\; \alpha_a \;+\; \gamma_{m,t} \;+\; \varepsilon_{iamt} \tag{1}$$

where y_{iamt} is an adult outcome of individual i with mother a born in municipality m who was t years old when PBF began. The key independent variable is an interaction between the mother-level binary treatment defined above, $Treat_a$, and a set of age t indicators I_t ranging from 10 to 34 years old. We normalize $\mu_{28} = 0$ since adult outcomes are mostly determined "children" aged 28 when the program began. With mother fixed effects α_a, our design leverages only within-family variation, absorbing other forms of selection.

To rule out the possibility of capturing the effects of phenomena other than PBF, we add two more terms in Equation 1. First, city-by-cohort fixed effects ($\gamma_{m,t}$) account for convergence in outcomes across Brazil's regions during the period. Still, even within a city-cohort group, there could be differences (other than PBF) between rich and poor households confounding adult outcomes, such as contemporaneous welfare policies. Hence, we interact our treatment indicator $Treat_a$ with a vector of city-by-cohort measures of exposure to other policies of the period, $\mathbb{X}'_{mt}$. Specifically, we control for the supply of secondary schools, the expansion of higher education establishments, and the roll-out of a major health program targeted at poor families. Finally, we cluster the error term ε_{imt} at the family level.

Hence, our identifying assumption is that, conditional on exposure to other policies, absent the creation of PBF trends in siblings differences between poorer versus richer households within the same municipality would remain the same. We show that this assumption is strongly supported by parallel trends for cohorts too old to benefit from PBF. If this design captures the effect of PBF, the intention-to-treat (ITT) estimates μ_t should be decreasing in age and indistinguishable from zero for cohorts too old to benefit from the program.

4 Results

4.1 PBF Long-term Effects

Figure 1 plots μ_t coefficients from Equation 1 for four key long-term outcomes. The absence of pre-trends for individuals impacted by the program after 24 years old and the larger effects for children who spent more time under PBF reinforce the credibility of our research design. Figures 2(a)–2(d) summarize our main findings: PBF promoted human capital accumulation for its beneficiaries, leading to reduced dependency on the social safety net, higher earnings, and intergenerational income mobility among the next generation.

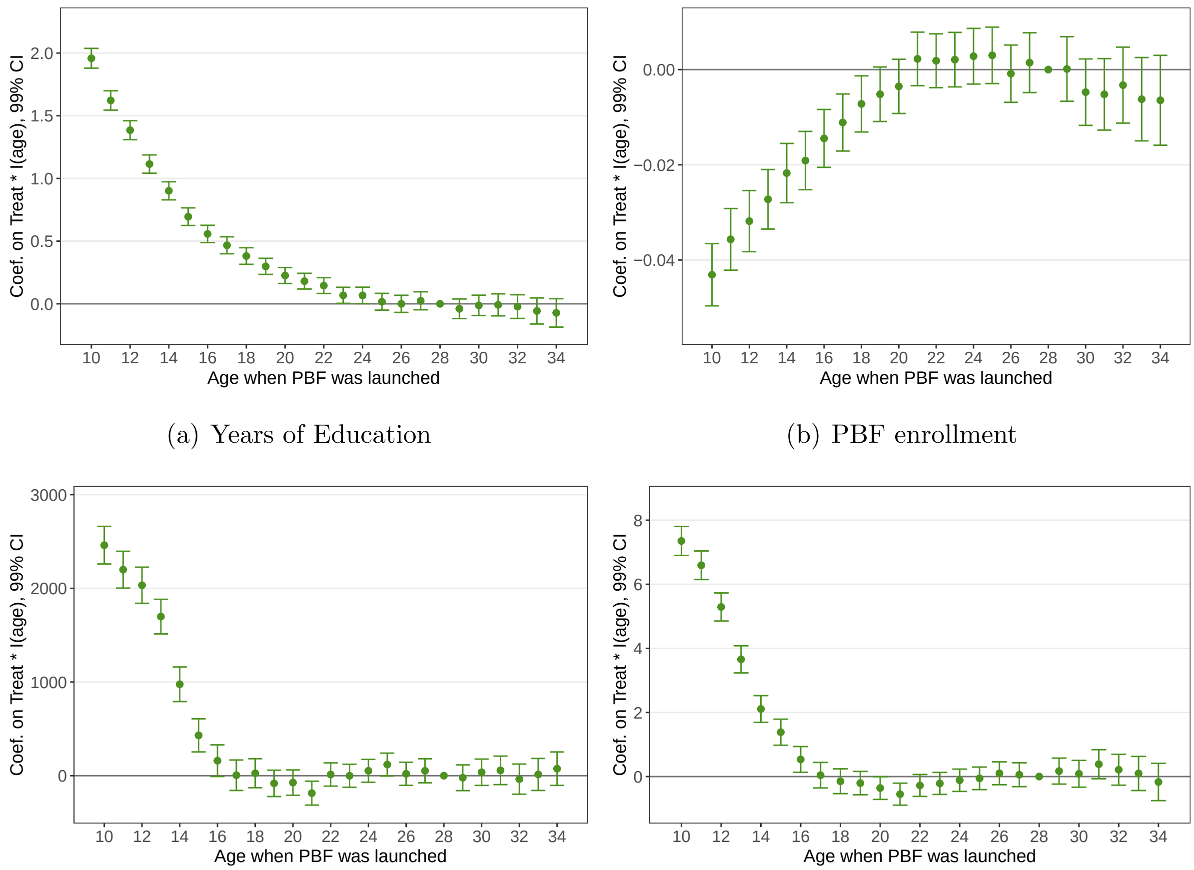
Figure 2(a) shows ITT estimates for total years of education. High exposure to PBF is associated with gains in educational attainment ranging from less than 0.5 years for young adults aged 18–22 at the start of the program to up to 2 years for children aged 10 when PBF began. Notably, there is no discernible effect for individuals older than 24 years old, as they had likely completed their educational trajectory before the program's implementation.

Similarly, Figure 2(b) reveals that children and young adults exposed to the program are less likely to be PBF beneficiaries in adulthood, indicating improved social mobility. Furthermore, Figure 2(c) shows that exposed children have higher earnings in the formal labor market, and Figure 2(d) document that they also achieve higher positions at the income distribution – a clear sign of intergenerational mobility. Notably, the effects on earnings and income mobility depicted in Figures 2(c) and 2(d) only arise for children aged 15 or younger when the program started.

In summary, Figures 2(a)–2(d) underscore that PBF is associated with long-term improvements in human capital and socio-economic well-being, suggesting the program's effectiveness in promoting sustained social mobility. Nevertheless, the different age patterns across outcomes might indicate the presence of both income and substitution effects (Garcia and Saavedra, 2023). To explore this further and delve into mechanisms, we analyze several adult outcomes across five dimensions: Human Capital, Labor Market, Intergenerational

Mobility, Migration, and Health and Behavior.

Figure 1: PBF effects in the Long Run: ITT event studies



(a) Years of Education

(b) PBF enrollment

(c) Formal Income

(d) Income Rank

Notes: The figure shows ITT coefficients μ_t and 99% confidence intervals obtained from Equation 1. A detailed description of outcomes used as dependent variables is given in Appendix Table A.1.

Table 2 displays ITT estimates obtained from gender-specific regressions. We report coefficients from a modified version of Equation 1, replacing age indicators with indicators for being 10–15 years old in 2004, 16–21 years old, or older. This approach allows us to compare cohorts that experienced both the income shock and PBF's conditionalities (10–15) to those only impacted by the cash transfer (16–21). From now on, we refer to these two groups as "fully-treated" and "partially-treated", respectively. The young adults older than 21 serve as control cohorts, based on the graphical evidence from event studies in Figure 1.

4.1.A Human Capital

Human Capital accumulation is key for CCTs, as the design of such programs relies on the assumption that allowing poor children to spend more time in school will foster the development of skills that enable sustained social mobility in the long-term. Panel A of Table

2 displays ITT estimates for years of education and the likelihoods of completing school (high school degree) and obtaining a college degree. Columns 1 and 3 of Table 2 reveal that fully-treated boys and girls attain 0.7 and 0.9 more years of education, respectively. In Appendix Table B.3 we compute counterfactuals for children by adjusting the baseline outcome in the treatment group by the relative change across cohorts in the control group. As children in the treatment group are around 50 percentage points (p.p.) more likely to participate in PBF, these estimates translate into educational gains of 1.3 years (14%) for boys and 1.9 years (19%) for girls after effects are inflated and normalized relative to the counterfactual.[10]

These improvements in educational attainment are evident in higher school completion rates: 9 p.p. (15%) for boys and 12 p.p. (21%) for girls. Nevertheless, the most substantial effects are observed in college degree attainment, where estimates range from 9 to 11 p.p., implying relative increases of more than 100% across all groups. On the other hand, estimates for years of education are substantially smaller for partially-treated young adults (columns 2 and 4 in Table 2), implying effects smaller than 5%. For this age group, the greater educational attainment arises primarily from increased school completion rates, with effects around 4 p.p. (5–6%).[11]

The economically significant effects suggest that PBF successfully increased the human capital of young generations in vulnerable households. The observed heterogeneity across cohorts, in turn, hints to different types of shocks experienced by younger versus older children. Partially-treated cohorts experience a household-level income shock, potentially reducing the opportunity cost of staying in school or seeking additional education. However, this late income shock is unlikely to promote the development of new skills in these young adults, who grew up under unfavorable conditions.[12] In contrast, fully-treated cohorts were exposed earlier and for longer to conditionalities that positively influenced educational and health outcomes related to the development of cognitive and non-cognitive skills, thus enhancing their ability to acquire human capital (Viana et al., 2018; Heckman and Mosso, 2014). This difference is reflected, for instance, in the steeper pattern for fully-treated kids in Figure 2(a) and the effects on college degree attainment in Table 2. Importantly, these heterogeneous effects on human capital accumulation might manifest in other dimensions, particularly in

[10]Henceforth in the paper, all absolute estimates refer to treatment on the treated (TOT) estimates obtained by inflating ITT estimates with participation rates. Also, estimates in relative terms refer to TOT estimates relative to counterfactuals listed in Appendix Table B.3.

[11]Our estimates of additional educational attainment are close to the 0.6–1.6 years reported by Parker and Vogl (2021) in the context of Mexico's *Progresa* for similarly-treated cohorts. The authors also find increases in school completion rates and larger effects for girls, but no effect on tertiary enrollment. However, given the different contexts and identification strategies, we avoid drawing strong conclusions from these comparisons.

[12]In particular, there is a large literature documenting that interventions in late childhood are rarely effective in promoting skill development for disadvantaged young adults (Heckman and Mosso, 2014).

the labor market.

4.1.B Labor Market

Panel B, columns 1 and 3, of Table 2 reveals that fully-treated children are more likely to work in the formal labor market. The increase in the probability of holding at least one formal job between 23–25 years old is 8 p.p. (14%) for boys and 14 p.p. (40%) for girls. The effects for the partially-treated (columns 2 and 4) are also positive but smaller, at around 5 p.p. (8–14%). Importantly, this increased labor supply is associated with higher earnings only for children impacted by the program's conditionalities (see Figure 2(c)). The gains are economically significant, amounting to around 2,300 BRL/year (30%) and 1,450 BRL/year (40%) for males and females, respectively.

Additionally, PBF is associated with substantial increases in entrepreneurial activity. The effects on the probability of opening a firm range from 0.5 to 2 p.p. for partially-treated and up to 6 p.p. for fully-treated cohorts. Given the low baseline, these imply large relative effects of 50% to 100%.

4.1.C Intergenerational Mobility

The ultimate goal of CCTs is sustained social mobility, i.e., breaking the intergenerational cycle of poverty. In the specific case of PBF, the program intended to *"allow the sustained emancipation of its participants"*. A straightforward manner to look into this is to check whether children in beneficiary households grow up to be adults that participate in PBF as heads of households themselves. As in Figure 2(b), panel C of Table 2 documents significant effects for fully-treated children. They are around 4 p.p. less likely to be part of the program in adulthood, or a 30% drop.

The smaller likelihood of depending on social welfare is in line with the higher formal earnings documented before. Despite these gains, given the substantial income inequality in Brazil, it could still be the case that children who grew up under PBF experience zero income mobility, remaining at the bottom of the income distribution. To investigate this further, we use the methodology in Britto et al. (2022a) to account for informal income and create cohort- and gender-specific income distributions. As shown in Figure 2(d), columns 1 and 3 of panel C in Table 2 demonstrate that fully-treated cohorts attain higher positions in their respective income distributions. The effects are around 6.3 (16%) and 4.3 (12%) percentiles for boys and girls, respectively. Besides impacting mean income ranks, PBF also affects probabilities of being in the tails of the income distribution. For instance, boys and girls are, respectively, 10.4 p.p. (15%) and 14 p.p. (23%) more likely to be outside the poorest 20% and 5.8 p.p. (69%) and 5.2 p.p. (87%) more likely to be among the richest 20%. Therefore, PBF promoted both the exit from poverty and extreme upward mobility, succeeding in its long-term goal of enabling sustained social mobility.

4.1.D Migration

In Panel D of Table 2, we explore PBF's effects on the migration and location decisions of children and young adults. Remarkably, we find substantial reductions in the probability of migration in both cohorts. Fully-treated children are 7 p.p. (17%) less likely to move away from their hometown, while the drop for partially-treated cohorts is approximately 4.5 p.p. (10%). These reductions are also pronounced when considering cross-state (2–3 p.p., 12.5%) and cross-regional (1–2 p.p., 10%) migrations. These findings align with existing empirical evidence, suggesting that welfare programs in Brazil can diminish the occurrence of "desperate" moves prompted by vulnerable socio-economic conditions.

Interestingly, for fully-treated children, reduced migration does not lead to a lower likelihood of living in a large urban area. On the contrary, this age group is on average around 4 p.p. (9%) more likely to reside in a city with more than 100k inhabitants. Conversely, partially-treated young adults exhibit a slightly lower propensity to live in large cities (1 p.p., 2%). This could be attributed to higher relocation costs for individuals with stronger connections to their hometowns. Additionally, this pattern might help explain why partially-treated cohorts observe a slight decrease in earnings and income rank, as migration to major urban centers often provides access to higher-paying job opportunities.

4.1.E Health and Behavior

Finally, panel E of Table 2 inspects outcomes related to health, broadly related to risky behavior. Fully-treated children are 0.5–1.0 p.p. (0.75%) more likely to survive up to 2019, suggesting overall better health conditions and reduced engagement in risky activities, particularly among boys. Notably, fully-treated girls exhibit a striking 2 p.p. (20%) decrease in the likelihood of childbearing before 18 years old. This finding is crucial as teenage pregnancy is pervasive among poor households in Brazil and has lasting implications throughout the life cycle and could be a key driver behind the human capital and income mobility gains we observe for girls.

Table 2: PBF effects in the Long Run: Age-specific ITT estimates by gender

	Males		Females	
	10–15	16–21	10–15	16–21
	(1)	(2)	(3)	(4)
% treated, Treated *vs.* Control	49.5	47.6	49.3	47.1
A. Human Capital				
Years of Education	0.663*** (0.023)	0.119*** (0.016)	0.918*** (0.024)	0.187*** (0.017)
School completion	0.047*** (0.003)	0.021*** (0.002)	0.060*** (0.003)	0.019*** (0.002)
College degree	0.046*** (0.002)	-0.003*** (0.001)	0.053*** (0.002)	-0.004*** (0.001)
B. Labor Market				
Formal Job	0.039*** (0.003)	0.027*** (0.002)	0.072*** (0.003)	0.025*** (0.002)
Months Worked	0.412*** (0.027)	0.286*** (0.019)	0.631*** (0.026)	0.137*** (0.018)
Formal Income (BRL/year)	1,298.3*** (77.8)	55.3 (47.4)	732.5*** (58.4)	-489.0*** (35.0)
Entrepreneurship	0.028*** (0.001)	0.006*** (0.001)	0.027*** (0.001)	0.008*** (0.001)
C. Intergenerational Mobility				
Adult PBF enrollment	-0.007*** (0.001)	-0.003*** (0.0008)	-0.030*** (0.003)	-0.001 (0.002)
Income pct. rank	3.29*** (0.151)	-0.465*** (0.103)	2.15*** (0.143)	-0.538*** (0.096)
Income rank > 20	0.054*** (0.002)	-0.023*** (0.002)	0.070*** (0.002)	-0.010*** (0.002)
Income rank > 80	0.029*** (0.002)	0.004**(0.001)	0.026*** (0.002)	-0.003*(0.001)
D. Migration				
City Migration	-0.035*** (0.003)	-0.024*** (0.002)	-0.035*** (0.003)	-0.019*** (0.002)
State Migration	-0.021*** (0.002)	-0.013*** (0.001)	-0.018*** (0.002)	-0.010*** (0.001)
Region Migration	-0.015*** (0.002)	-0.010*** (0.001)	-0.011*** (0.001)	-0.006*** (0.001)
Live in Metro Area	0.014*** (0.002)	-0.010*** (0.002)	0.021*** (0.002)	-0.006*** (0.002)
E. Health and Behavior				
Survive up to 2019	0.004*** (0.001)	0.001* (0.001)	0.002*** (0.001)	0.001** (0.000)
Teenage parenthood	-0.002 (0.001)	0.001* (0.001)	-0.010*** (0.002)	0.007*** (0.002)
Observations	11,386,335	11,386,335	11,381,264	11,381,264

Notes: The table reports ITT coefficients on interactions of cohort indicators and our treatment variable. They are obtained from a modified version of Equation 1 in which age indicators I_t are replaced by indicators for being 10–15, 16–21, or older (omitted category) when PBF began. We run separate regressions for males and females. A detailed description of outcomes used as dependent variables is given in Appendix Table A.1. (*p<0.1; **p<0.05; ***p<0.01).

4.2 Racial and Regional Heterogeneity

Appendix Tables B.1 and B.2 report ITT estimates by race (whites versus non-whites) and region (Center-South versus North and Northeast). Across all adult outcomes we consider, we find relative effects to be larger among the more disadvantaged group, that is, children who are non-white and born in the North and Northeast regions of the country. This goes in hand with the focused approach of PBF, which aims at targeting the most vulnerable groups in society. Moreover, by moving up poor children but moving relative more to those in more underprivileged groups, PBF can be (cautiously) interpreted as force reducing racial and regional disparities in income mobility – such as those documented in Britto et al. (2022a).

4.3 Heterogeneity in PBF Effectiveness

As noted in Garcia and Saavedra (2023), a key assumption behind CCTs' design is that relaxing demand-side constraints such as children's opportunity cost of time will result in increased human capital acquisition. However, in many contexts the supply of schooling – schools, teachers, textbooks – is insufficient. Analogously, increased human capital is a necessary but not sufficient condition for income mobility, as it is usually related to the local availability of opportunities.(Britto et al., 2022a; Chetty et al., 2014) In this context, PBF could display heterogeneous effects according to family characteristics related to the relaxing of demand-side constraints and according to place supply-side inputs, such as educational infrastructure.

Table 3: PBF effects in the Long Run: Heterogeneity by Family and Place Inputs

	Mothers' Education		City's School Quality	
	Low	High	Low	High
	(1)	(2)	(3)	(4)
A. Human Capital				
Years of Education	0.329*** (0.019)	1.08*** (0.050)	0.971*** (0.026)	0.763*** (0.016)
School completion	0.027*** (0.002)	0.076*** (0.005)	0.064*** (0.003)	0.055*** (0.002)
College degree	0.019*** (0.002)	0.061*** (0.005)	0.054*** (0.002)	0.050*** (0.001)
B. Labor Market				
Formal Income (BRL/year)	299.7*** (61.7)	1,206.2*** (148.6)	808.9*** (69.4)	1,239.0*** (50.0)
Entrepreneurship	0.016*** (0.001)	0.024*** (0.003)	0.020*** (0.001)	0.032*** (0.001)
C. Intergenerational Mobility				
Adult PBF enrollment	-0.013*** (0.002)	-0.016*** (0.004)	-0.021*** (0.002)	-0.018*** (0.001)
Income pct. rank	0.389*** (0.135)	3.43*** (0.324)	1.02*** (0.155)	3.66*** (0.104)
D. Migration				
City Migration	-0.025*** (0.002)	-0.049*** (0.006)	-0.039*** (0.003)	-0.037*** (0.002)
Live in Metro Area	0.002 (0.002)	0.024*** (0.005)	0.014*** (0.001)	0.019*** (0.002)
E. Health and Behavior				
Teenage parenthood	-0.006*** (0.002)	-0.005 (0.003)	-0.007*** (0.002)	-0.009*** (0.001)

Notes: The table reports ITT coefficients on interactions of cohort indicators and our treatment variable. They are obtained from a modified version of Equation 1 in which age indicators I_t are replaced by indicators for being 10–15, 16–21, or older (omitted category) when PBF began. We run separate regressions for each group. A detailed description of outcomes used as dependent variables is given in Appendix Table A.1. (*p<0.1; **p<0.05; ***p<0.01).

To gauge this, we look for heterogeneity in long-term effects according to family and place inputs. Table 3 reports ITT estimates for fully-treated children, i.e., those aged 10–15 years old when exposed to the program. Columns 1 and 2 contrast the effects for poor children whose mothers were below or above the median educational attainment, respectively. Remarkably, human capital and intergenerational mobility effects are substantially larger for children of mothers with relatively higher education. In turn, columns 3 and 4 compare outcomes for children growing up in cities below and above the median level of (pre-PBF) public school quality, respectively. Despite similar effects for human capital attainment in both groups, labor market, and intergenerational mobility effects are significantly higher in cities with better infrastructure.

5 Conclusion

In conclusion, this paper provides robust evidence on the long-term impacts of Brazil's *Programa Bolsa Família* (PBF), the largest Conditional Cash Transfer (CCT) program in the world. Remarkably, our findings demonstrate that PBF successfully achieves its goal of promoting sustained social mobility among the next generation.

Children exposed to PBF's conditionalities between ages 10 and 15 experienced significant gains in education, with notable increases in high school completion and college degree attainment. Additionally, PBF was associated with improved income mobility, enabling beneficiaries to rise in income distribution and escape poverty. The program also displayed positive impacts on labor market participation, earnings, and reduced dependence on social assistance, debunking the notion of long-term dependency on CCTs. Moreover, we find indirect effects on educational attainment and labor supply for young adults aged 16–21 when PBF began – suggesting spillovers to other household members impacted by the cash transfer. However, young adults do not observe improvements in earnings or social mobility, highlighting the role of conditionalities in breaking the intergenerational cycle of poverty.

The paper's comprehensive analysis fills a gap in the literature, providing much-needed insights into the intergenerational impact of CCT programs (Molina Millán et al., 2019; Parker and Vogl, 2021; Garcia and Saavedra, 2023). These findings have significant implications for policymakers in both developing and developed countries, offering valuable lessons for designing effective poverty reduction strategies in a world of growing inequality (Blattman et al., 2017; Gentilini et al., 2020).

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Online Appendix to "Do CCTs Create Conditions to Thrive? *Bolsa Família* and Social Mobility in Brazil"

Britto, Fonseca, Pinotti, Sampaio and Warwar

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A Appendix to Section 3

A.1 Definition of Outcomes

Table A.1: Description of Outcome Variables

Outcome	Sources and Description
A. Human Capital	
Years of Education	Calculated from educational level reported in administrative employment registries (RAIS) or welfare registries (CadÚnico), in this order of priority. We go from education level to years of education using the standard grade progression in Brazil.
School completion	Dummy equal to 1 if years of education is greater or equal than 12.
College degree	Dummy equal to 1 if years of education is greater or equal than 16.
B. Labor Market	
Formal Job	Dummy equal to 1 if held at least one formal job (RAIS) btw 23–25 years old.
Months Worked	Average months worked per year in a formal job (RAIS) btw 23–25 years old.
Formal Income (BRL/year)	Average annual earnings in formal jobs (RAIS) btw 23–25 years old.
Entrepreneurship	Dummy equal to 1 if has firm registered on the Firm Registry (CNPJ)
C. Intergenerational Mobility	
Adult PBF enrollment	Dummy equal to 1 if head (or her partner) in HH receiving PBF in 2015–19.
Income pct. rank	Income percentile in the gender and cohort-specific income distribution as computed in Britto et al. (2022a)
Income rank > 20	Dummy equal to 1 if income percentile greater than 20
Income rank > 80	Dummy equal to 1 if income percentile greater than 80
D. Migration	
City Migration	Dummy equal to 1 if city of residence in 2019 is different from city of birth (defined as mother's city in 2003). Residence is tracked by updates in the Person Registry (CPF).
State Migration	Dummy equal to 1 if state of residence is different from state of birth
Region Migration	Dummy equal to 1 if region of residence is different from region of birth
Live in Metro Area	Dummy equal to 1 if city of residence has population of 100k or more
E. Health and Behavior	
Survive up to 2019	Dummy equal to 1 alive in 2019, tracked by updated in CPF
Teenage parenthood	Dummy equal to 1 if registers a child in CPF before 18 years old

B Appendix to Section 4

B.1 Racial and Regional Heterogeneity

Table B.1: PBF effects in the Long Run: Age-specific ITT estimates by race

	Whites		Non-Whites	
	10–15	16–21	10–15	16–21
	(1)	(2)	(3)	(4)
A. Human Capital				
Years of Education	0.359*** (0.014)	0.197*** (0.010)	0.943*** (0.024)	0.167*** (0.016)
School completion	0.031*** (0.002)	0.027*** (0.002)	0.062*** (0.002)	0.018*** (0.002)
College degree	0.037*** (0.002)	-0.001 (0.001)	0.050*** (0.002)	-0.001 (0.001)
B. Labor Market				
Formal Income (BRL/year)	807.1*** (70.1)	-25.0 (44.8)	925.1*** (55.4)	-186.1*** (32.8)
Entrepreneurship	0.031*** (0.001)	0.009*** (0.001)	0.019*** (0.001)	0.003*** (0.001)
C. Intergenerational Mobility				
Adult PBF enrollment	-0.018*** (0.002)	-0.005*** (0.001)	-0.018*** (0.002)	-0.002 (0.001)
Income pct. rank	1.47*** (0.135)	-0.261*** (0.094)	2.91*** (0.130)	-0.703*** (0.087)
D. Migration				
City Migration	-0.035*** (0.002)	-0.026*** (0.002)	-0.033*** (0.002)	-0.018*** (0.002)
Live in Metro Area	-0.009*** (0.002)	-0.009*** (0.001)	0.032*** (0.002)	-0.003** (0.001)
E. Health and Behavior				
Teenage parenthood	-0.010*** (0.002)	0.001 (0.001)	-0.006*** (0.002)	0.004*** (0.001)
Observations	11,806,187	11,806,187	10,961,412	10,961,412

Table B.2: PBF effects in the Long Run: Age-specific ITT estimates by region

	Center-South		North and Northeast	
	10–15	16–21	10–15	16–21
	(1)	(2)	(3)	(4)
A. Human Capital				
Years of Education	0.700*** (0.016)	0.116*** (0.012)	1.10*** (0.026)	0.211*** (0.017)
School completion	0.052*** (0.002)	0.021*** (0.001)	0.069*** (0.002)	0.020*** (0.002)
College degree	0.047*** (0.001)	-0.006*** (0.001)	0.062*** (0.002)	0.001 (0.001)
B. Labor Market				
Formal Income (BRL/year)	1,229.9*** (49.9)	-135.0 (32.2)	857.7*** (69.0)	-318.5*** (38.8)
Entrepreneurship	0.031*** (0.001)	0.010*** (0.001)	0.023*** (0.001)	0.005*** (0.001)
C. Intergenerational Mobility				
Adult PBF enrollment	-0.018*** (0.001)	-0.003*** (0.001)	-0.020*** (0.002)	-0.002 (0.002)
Income pct. rank	3.66*** (0.103)	-0.593*** (0.073)	1.20*** (0.156)	-0.422*** (0.102)
D. Migration				
City Migration	-0.038*** (0.002)	-0.025*** (0.001)	-0.037*** (0.003)	-0.021*** (0.002)
Live in Metro Area	0.014*** (0.002)	-0.009*** (0.001)	0.027*** (0.002)	-0.009** (0.002)
E. Health and Behavior				
Teenage parenthood	-0.010*** (0.002)	0.001 (0.001)	-0.005*** (0.002)	0.006*** (0.001)
Observations	16,466,417	16,466,417	6,301,182	6,301,182

B.2 First-stage relationships and outcomes counterfactuals

Table B.3: First-stage relationships and outcomes counterfactuals by gender

	Males		Females		Whites		Non-Whites	
	10–15	16–21	10–15	16–21	10–15	16–21	10–15	16–21
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
% treated	49.5	47.6	49.3	47.1	46.1	44.0	50.3	47.8
# years treated	3.81	1.27	3.81	1.26	3.25	1.14	4.07	1.31
A. Human Capital								
Years of Education	9.6	10.3	9.7	10.4	11.1	11.2	9.1	10.4
School completion	0.60	0.63	0.58	0.61	0.71	0.70	0.54	0.61
College degree	0.06	0.07	0.10	0.13	0.10	0.12	0.07	0.10
B. Labor Market								
Formal Job	0.58	0.61	0.35	0.36	0.62	0.61	0.43	0.46
Months Worked	4.5	4.9	2.7	2.7	5.0	5.0	3.2	3.5
Formal Income (BRL;year)	7,503	7,652	3,564	3,308	8,022	7,564	5,162	5,028
Entrepreneurship	0.03	0.04	0.02	0.03	0.03	0.05	0.03	0.03
C. Intergenerational Mobility								
Adult PBF enrollment	0.03	0.04	0.31	0.48	0.14	0.20	0.18	0.31
Income pct. rank	38.3	38.1	35.3	34.7	49.8	46.6	31.1	32.5
Income rank > 20	0.68	0.70	0.61	0.62	0.85	0.80	0.53	0.61
Income rank > 80	0.09	0.09	0.06	0.06	0.13	0.11	0.06	0.05
D. Migration								
City Migration	0.43	0.46	0.42	0.44	0.46	0.49	0.41	0.42
State Migration	0.20	0.21	0.18	0.18	0.21	0.23	0.18	0.17
Region Migration								
Live in Metro Area	0.43	0.45	0.42	0.45	0.50	0.50	0.40	0.44
E. Health and Behavior								
Survive up to 2019	0.98	0.97	0.99	0.99	0.99	0.99	0.99	0.98
Teenage parenthood	0.01	0.03	0.11	0.17	0.06	0.09	0.06	0.11

Notes: The table reports ITT long-term effects of childhood exposure to PBF, for children aged 5 to 14 years old when PBF started. (*p<0.1; **p<0.05; ***p<0.01).

B.3 Robustness to Alternative Treatment Definitions