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Do CCTs create conditions to thrive? Bolsa Família and social mobility in Brazil

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Do CCTs create conditions to thrive? *Bolsa Família* and social mobility in Brazil

Diogo G. C. Britto,¹ Alexandre Fonseca,² Paolo Pinotti,³ Breno Sampaio,⁴ and Lucas Warwar⁵

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Abstract: Conditional cash transfers (CCTs) are widely used as a poverty reduction policy. While a large stream of literature has evaluated their short-term impacts, we know far less about their long-term effects. This paper investigates the long-term, intergenerational effects of one of the largest CCT in the world: Brazil's Programa Bolsa Família (PBF). To estimate PBF long-term effects, we compare adult outcomes of siblings more and less exposed to the programme due to their age in families targeted and not by the programme using a difference-in-differences design and a comprehensive set of population-wide administrative datasets. We show that PBF significantly increases human capital accumulation, earnings, and intergenerational income mobility, and that it reduces welfare dependency by the next generation. These effects are more pronounced for younger children and women, highlighting the importance of early exposure to the programme. Our findings underscore the effectiveness of PBF in breaking the intergenerational cycle of poverty and fostering social mobility.

Key words: cash transfers, poverty, long-term effects

JEL classification: H53, I38

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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, they aim to immediately alleviate poverty and ease financial constraints. At the same time, families must comply with educational and health requirements for their children, which have the aim of ensuring better long-term outcomes for children and breaking the intergenerational cycle of poverty. While several studies document that CCTs are effective in the short-term (Fiszbein et al. 2009; Bastagli et al. 2019), far less robust evidence is available on the long-term effects of CCTs and their effectiveness in breaking the poverty cycle (Molina Millán et al. 2019; Garcia and Saavedra 2023).

In this paper, we estimate the long-term effects of one of the largest CCT programme in the world, Brazil's *Programa Bolsa Família* (PBF). Created in 2003, PBF is the main welfare programme in the country, assisting over 14 million households as of 2019. Previous studies have provided evidence that PBF had positive short-term impacts on poor children's education and health outcomes (Viana et al. 2018). However, the main purpose of the programme was to provide conditions for these kids to escape poverty in adulthood. In this paper, we combine different administrative datasets tracking adult outcomes for over 20 million people born between 1970 and 1994 to ask whether individuals exposed to PBF during childhood display improved socioeconomic conditions later on. Large-scale assessments of CCTs long-term impacts remain rare in the literature and key for policy-making in both developing and developed countries (Blattman et al. 2017; Gentilini et al. 2020).

We employ a difference-in-differences (DID) design to estimate the long-term effects of PBF on children's long-term outcomes. Specifically, our first difference compares (treated) cohorts who were young enough to benefit from the programme to older (control) cohorts who were not exposed to the programme while growing up. The second difference compares children in families who were exposed and not to the programme – essentially, a comparison between poorer and richer households. Hence, our DID design compares the outcomes of younger and older children in families exposed to PBF, relative to the differences observed in richer families, not exposed to the programme, in order to absorb cohort effects – similar to previous studies on the long-term effects on social safety net programmes in the US (Goodman-Bacon 2021; Bailey et al. 2024). Importantly, we refine these comparisons in two key ways. First, our specification includes fine family fixed effects so that the comparison between younger and older cohorts leverages only variation between siblings. Second, our analysis also includes municipality by cohort fixed effects so that the comparison between poorer and richer families, exposed and not to the programme, leverages only within municipality-cohort variation. Hence, our specification avoids comparisons across poorer and richer areas so that our results cannot be explained by economic convergence across areas. Finally, we control for the rollout

of other relevant government programmes contemporaneous to PBF and disproportionately affecting poorer families.

An important aspect of our analysis is that we identify exposure to the programme based on families' pre-determined characteristics. Hence, we net out potential behavioural changes in family income (or reported income) that may be endogenous to PBF.¹ Specifically, we train a machine learning (ML) model that identifies households' likelihood to participate in the programme based on families' pre-determined characteristics.² Using the ML model predictions, we split families into a high-exposure units that define the treatment groups and low-exposure ones that define the control group.

Our main result is that PBF significantly increased human capital accumulation for its beneficiaries, leading to substantial income gains and upward mobility for beneficiary children. We first document that boys and girls exposed to the programme's conditionalities between ages 10–15 attain, on average, 1.3 and 1.9 more years of education, respectively. This implies a 14% and 19% gain in completed years of schooling relative to their baseline counterfactual, respectively.³ The educational gains translate into higher chances of completing high school – around +9 p.p. (15%) for boys and +12 p.p. (21%) for girls –, and, remarkably, in a substantial increase in the probability of completing a college degree, which increases by nearly 5 p.p. 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 programme. However, such gains are fully concentrated on higher high school completion rates, with no improvements in the probability of completing college.

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 programme's conditionalities.⁴ In turn, the effects on older children (16–21) cannot be explained by the conditionalities and are more plausibly explained by the programme's income transfers which may allow older individuals to increase educational investments – e.g., by pursuing adult education programmes

¹ Total family income per capita, comprising formal and informal income sources is the sole determinant of eligibility to PBF.

² 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.

³ 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.

⁴ This is true in our setting which analyses effects on children impacted in the first years of the programme. In 2008, a slight reform introduced schooling conditionalities for children aged 16–17 years old, but did not affect children in our sample.

offering a fast track for the completion of high school.⁵ 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 labour market – but increased labour supply is associated with higher earnings only for children impacted by the programme's conditionalities. In particular, boys and girls aged 10–15 at the start of the programme 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 children exposed from ages 16-21 is around 3 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 exposed to PBF transfers are 4 p.p. less likely to participate in the programme as adults, or a 30% drop relative to their baseline counterfactual. This result is an important indication that PBF promoted social mobility and goes against the common-held argument that CCTs generate long-term welfare dependency.

Given the high level of labour informality in Brazil, we attempt to estimate PBF on total income, considering both formal and informal income sources. Hence, we aim to move beyond our initial analysis solely focusing on formal labour income which can be accurately measured in administrative employment data. To do so, we use a ML learning model trained on large household surveys, tracking formal and informal income, to estimate informal income for individuals in our data. We follow the methodology by Britto, Fonseca, et al. (2022) who studies inter-generational mobility in Brazil. We combine the estimates for informal income with the formal labour income observed in the administrative data to create a measure of total individual income. Then, we define the position of each individual in the income distribution relative to their own cohort, and estimate the impacts of PBF on this measure. We find that PBF significantly increase the income position of exposed children, but again only for those directly impacted by its conditionalities. Boys and girls exposed to the programme rank, respectively, 6.3 and 4.3 percentiles higher in the 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 exit from poverty and extreme upward mobility, succeeding in its long-term goal of enabling sustained social mobility.

⁵ Although high school completion in Brazil is expected at age 18, significant levels of grade distortion – especially among the poor – can help explain the effects on young adults above age 18. Moreover, the possibility of seeking supplementary education later in life also explains part of the observed effects.

Furthermore, we show that PBF is related to significant reductions in migration rates across cohorts, which relates to anecdotal and empirical evidence of welfare programmes lessening the need for forced economic migration among the extremely poor in Brazil. We also find that girls exposed to the programme 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 programme.

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 non-whites 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 programme 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 programme. 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 positively impacted a wide range of long-term outcomes. Young children exposed to the programme experienced lasting improvements in education and earnings, climbing up the income distribution. The fact that the effects are concentrated on younger children, exposed to PBF's school requirements suggest that CCTs' conditionalities might be a crucial component for programme success in breaking the poverty cycle.

Our work contributes to a long literature studying the impacts of CCT programmes – for a review, see Fiszbein et al. (2009); Bastagli et al. (2019); Molina Millán et al. (2019); Garcia and Saavedra (2023). While short-term effects on various outcomes have been extensively studied, comprehensive assessments of long-term effects and the effectiveness of CCTs in breaking the poverty cycle are more rare. Such evaluations are challenging for various reasons. First, it is necessary to wait for several years after programme implementation so that the first cohorts of treated children enter adulthood. Second, it is often challenging to find suitable controls for evaluating causal long-term effects. This is the case even for programmes that have been randomized at their introduction, since these programmes are typically extended to the

full target population a few years after randomization. Our results relates to different previous contributions studying the long-term impacts of CCT programme. Using admin data, Attanasio et al. (2021) shows that a Colombian CCT improved education and led to reduction in crime and teenage pregnancy, while Cahyadi et al. (2020) shows that a randomized CCT led to sustain gains in education for children. In turn, using a 10% sample of the Mexican Population Census, Parker and Vogl (2023) shows that girls exposed for longer to *Progresa* achieved higher education, income, and economic standards, while the effects on boys were not statistically significant. In a similar setting to ours, Laguinde et al. (2025) provides an evaluation of PBF showing that children cohorts exposed for longer to the programme achieved better education and labour market outcomes.

We contribute to this literature by providing one of the first comprehensive analysis based on an unique combination of large-scale datasets, rarely available in the context of developing countries. Using these data, we devise a measure of CCT exposure within a DID framework to estimate impacts on a wide range of outcomes. We show that PBF led to substantial improvements over different dimensions such as education, income, welfare dependency, and other important socioeconomic outcomes, e.g., teenage pregnancy and mortality. Our detailed data allow us to strongly refine our econometric specification, for example, leveraging within families comparisons across siblings. Hence, we provide robust evidence that PBF strongly contributed to breaking the poverty cycle in Brazil.

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. 2024; 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 programme. 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.

2 Institutional background

2.1 The *Programa Bolsa Família* (PBF)

PBF was created in October 2003 and soon became one of the largest CCT programme in the world. As of 2019, it reached 15 million families – roughly 30% of the population – with an average transfer of 180 BRL per family, costing 0.5% of the Brazilian GDP annually. It is broadly considered a successful programme 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. Families with per capita income less than half of the poverty threshold receive an additional, unconditional monthly benefit of 70 BRL. Eligible households can self-enroll at a social assistance center or be prospected to the programme 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 programmes are based on the assumption that they improve human capital acquisition by helping households overcome demand-side constraints such as educational externalities, informational constraints, and the 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

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.

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 programme’s design.

3 Data and methodology

3.1 Data

We combine several administrative records to perform our analysis. First, we use 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. Our analysis focuses on children born between 1970 and 1994 (aged 10 to 34 years old when PBF started) 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 programme’s payments from 2004 to 2020. We observe children’s educational and labour 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 from firm registry data (CNPJ). We observe fertility, migration, and location decisions using the CPF registry. Finally, we follow the methodology in Britto, Fonseca, et al. (2022) to estimate informal income. Specifically, we train machine learning models on survey data – PNAD household surveys and the Brazilian Population Censuses – to predict informal income based on an array of characteristics that can be observed both in the survey data and our sample based on administrative data.⁸

3.2 Empirical strategy

We expect PBF’s long-term effects to be higher for children impacted at younger ages. At the same time, by construction, older cohorts outcomes measured before PBF implementation in 2003 cannot be affected by the programme. Accordingly, we use a differences-in-differences

⁷ Due to accumulation of surnames, around 52% of Brazilians have a unique name. In Britto, Pinotti, and Sampaio (2022), 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 A1.

setup in which temporal variation comes from cohorts born earlier versus later relative to PBF implementation. We measure family-level exposure to PBF to define the treatment and control groups in our analysis. Specifically, we compare long-term outcomes of children young enough to benefit from the programme with their older siblings (first difference) in families with high and low probability of receiving PBF transfers (second difference).

We identify families' exposure to PBF by predicting their likelihood to participate in the programme 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 labour income, and city of residence as features. Importantly, all time-varying covariates are measured before the start of PBF. Exposure to the programme is defined by the probability of PBF enrollment in 2004. Table 1 shows mothers' characteristics by deciles of their predicted "PBF score", showing that highly-exposed mothers 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 – while the control group is defined by the remaining children.⁹

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

Note: 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 programme:

$$y_{iamt} = \sum_{t=10}^{34} (I_t \times Treat_a) \mu_t + Treat_a \vec{X}'_{mt} \Omega + \alpha_a + \gamma_{m,t} + \varepsilon_{iamt} \quad (1)$$

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

⁹ In Appendix Table A5, we show that our results are robust to alternative treatment definitions.

34 years old. We normalize $\mu_{28} = 0$ since most adult outcomes we study are essentially determined before age 28 – for example, individuals very rarely pursue formal education above this age. The mother fixed effects (α_a) ensure that 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. For example, contemporaneous social policies could disproportionately affect younger cohorts and contribute to reducing the gap between rich and poor children. Hence, we interact our treatment indicator $Treat_a$ with a vector of city-by-cohort measures of exposure to other policies of the period, $\vec{X}'_{mt}$. Specifically, we control for the supply of secondary schools, the expansion of higher education establishments, and the roll-out of a major health programme targeted at poor families. Finally, we cluster the error term ε_{imt} at the family level, which matches the level of the variation that we exploit in exposure to the PBF.

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 programme.

4 Results

4.1 PBF long-term effects

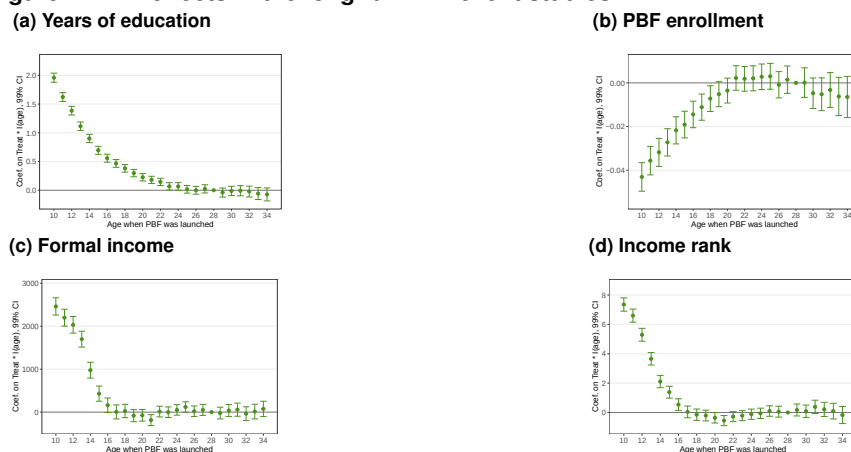
Figure 1 plots μ_t coefficients from Equation 1 for four key long-term outcomes. The absence of pre-trends for individuals impacted by the programme after 24 years old and the larger effects for children who spent more time under PBF reinforce the credibility of our research design. Figures 1a–1d summarize 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 1a 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 programme 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 programme’s implementation. Sim-

ilarly, Figure 1b reveals that individuals exposed to PBF are less likely to be PBF beneficiaries in adulthood, indicating improved social mobility. Furthermore, Figure 1c shows that exposed children have higher earnings in the formal labour market, and Figure 1d 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 1c and 1d only arise for children aged 15 or younger when the programme started.

In summary, Figures 1a–1d underscore that PBF is associated with long-term improvements in human capital and socio-economic well-being, suggesting its 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 assess this, we analyze adult outcomes across five dimensions: human capital, labour market, intergenerational mobility, migration, health and fertility.

Figure 1: PBF effects in the long run: ITT event studies



Note: 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 A1.

Source: Authors' illustration.

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.

Human capital

Human Capital accumulation is key for CCTs, as the design of such programmes 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 de-

gree) 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 A2 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. 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 A2.

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%).¹⁰

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.¹¹ 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 1a 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 the labour market.

¹⁰ Our estimates of additional educational attainment are close to the 0.6–1.6 years reported by Parker and Vogl (2023) in the context of Mexico’s *Progres*a 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.

¹¹ 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).

Labour market

Panel B, columns 1 and 3, of Table 2 reveals that fully-treated children are more likely to work in the formal labour 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 labour supply is associated with higher earnings only for children impacted by the programme's conditionalities (see Figure 1c). 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%.

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 programme 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 1b, 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 programme 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, Fonseca, et al. (2022) to account for informal income and create cohort- and gender-specific income distributions. As shown in Figure 1d, 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.

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 programmes 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.

Health and behaviour

Finally, panel E of Table 2 inspects outcomes related to health, broadly related to risky behaviour. 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 (1)	16–21 (2)	10–15 (3)	16–21 (4)
% treated, Treated vs. Control	49.5	47.6	49.3	47.1
<i>A. Human capital</i>				
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)
<i>B. Labour market</i>				
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)
<i>C. Intergenerational mobility</i>				
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)
<i>D. Migration</i>				
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)
<i>E. Health and behaviour</i>				
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

Note: 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_i 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 A1. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$).

4.2 Racial and regional heterogeneity

Appendix Tables A3 and A4 report ITT estimates by race (whites versus non-whites) and region (Center-South versus North and Northeast).¹² 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, Fonseca, et al. (2022).

¹² We track race by the modal race reported in employment and welfare registries, and as non-whites blacks (*pretos*), mixed (*pardos*), and indigenous people.

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, Fonseca, et al. 2022; 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 (1)	High (2)	Low (3)	High (4)
<i>A. Human capital</i>				
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)
<i>B. Labour market</i>				
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)
<i>C. Intergenerational mobility</i>				
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)
<i>D. Migration</i>				
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)
<i>E. Health and behaviour</i>				
Teenage parenthood	-0.006*** (0.002)	-0.005 (0.003)	-0.007*** (0.002)	-0.009*** (0.001)

Note: 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 and only report coefficients for children aged 10–15. A detailed description of outcomes used as dependent variables is given in Appendix Table A1. (*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 programme. 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, labour

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) programme 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 programme also displayed positive impacts on labour 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 labour 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 programmes (Molina Millán et al. 2019; Parker and Vogl 2023; 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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Appendix

A Appendix to Section 3

A1 Definition of outcomes

Table A1: Description of outcome variables

Outcome	Sources and description
<i>A. Human capital</i>	
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.
<i>B. Labour market</i>	
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)
<i>C. Intergenerational mobility</i>	
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, Fonseca, et al. 2022)
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
<i>D. Migration</i>	
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
<i>E. Health and behaviour</i>	
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

B1 First-stage relationships and outcomes counterfactuals

Table A2: First-stage relationships and outcomes counterfactuals

	Males		Females		Whites		Non-Whites	
	10–15 (1)	16–21 (2)	10–15 (3)	16–21 (4)	10–15 (5)	16–21 (6)	10–15 (7)	16–21 (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
<i>A. Human capital</i>								
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
<i>B. Labour market</i>								
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
<i>C. Intergenerational mobility</i>								
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
<i>D. Migration</i>								
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
<i>E. Health and behaviour</i>								
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

Note: The table reports first-stage relationships and outcomes counterfactuals by gender and race for fully- and partially-treated cohorts. First-stage relationships are the probability of being in a household treated by PBF in the first 3 years of the programme (2004–06) and the actual number of years between 0–21 years old spent under the programme. For each cohort, they are calculated as the difference between raw averages in the treatment and control groups in our research design. Counterfactual outcomes are computed as average outcomes for the non-exposed cohorts (older than 21 at the start of the programme) in the treatment group (baseline) adjusted by the relative change across cohorts in the control group (trend).

B2 Racial and regional heterogeneity

Table A3: PBF effects in the long run: Age-specific ITT estimates by race

	Whites		Non-Whites	
	10–15 (1)	16–21 (2)	10–15 (3)	16–21 (4)
<i>A. Human capital</i>				
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)
<i>B. Labour market</i>				
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)
<i>C. Intergenerational mobility</i>				
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)
<i>D. Migration</i>				
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)
<i>E. Health and behaviour</i>				
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

Note: 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 whites and non-whites. A detailed description of outcomes used as dependent variables is given in Appendix Table A1. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$).

Table A4: PBF effects in the long run: Age-specific ITT estimates by region

	Center-South		North and Northeast	
	10–15 (1)	16–21 (2)	10–15 (3)	16–21 (4)
<i>A. Human capital</i>				
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)
<i>B. Labour market</i>				
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)
<i>C. Intergenerational mobility</i>				
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)
<i>D. Migration</i>				
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)
<i>E. Health and behaviour</i>				
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

Note: 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 region. A detailed description of outcomes used as dependent variables is given in Appendix Table A1. (*p<0.1; **p<0.05; ***p<0.01).

B3 Robustness to alternative treatment definitions

Table A5: PBF effects in the long run: Robustness to alternative treatment definitions

	Top 25% (baseline)		Top 20%		Top 30%	
	10–15 (1)	16–21 (2)	10–15 (3)	16–21 (4)	10–15 (5)	16–21 (6)
<i>First stage</i>						
% treated	49.4	47.4	50.1	50.1	47.9	44.1
# years treated	3.81	1.27	4.00	1.37	3.65	1.16
<i>A. Human capital</i>						
Years of education	0.839*** (0.014)	0.165*** (0.010)	0.808*** (0.014)	0.166*** (0.010)	0.860*** (0.013)	0.160*** (0.009)
School completion	0.058*** (0.001)	0.022*** (0.001)	0.054*** (0.002)	0.020*** (0.001)	0.059*** (0.001)	0.022*** (0.001)
College degree	0.052*** (0.001)	-0.003*** (0.001)	0.049*** (0.001)	-0.003*** (0.001)	0.054*** (0.001)	-0.003*** (0.001)
<i>B. Labour market</i>						
Formal income (BRL/year)	1,114.5*** (40.2)	-208.0*** (24.9)	973.0*** (40.0)	-231.56*** (25.0)	1,191.7*** (41.1)	-201.9*** (25.1)
Entrepreneurship	0.029*** (0.001)	0.008*** (0.001)	0.027*** (0.001)	0.007*** (0.001)	0.030*** (0.001)	0.009*** (0.001)
<i>C. Intergenerational mobility</i>						
Adult PBF enrollment	-0.019*** (0.001)	-0.003*** (0.001)	-0.020*** (0.001)	-0.003*** (0.001)	-0.019*** (0.001)	-0.003*** (0.001)
Income pct. rank	2.94*** (0.086)	-0.504*** (0.059)	2.49*** (0.090)	-0.507*** (0.063)	3.24*** (0.083)	-0.521*** (0.057)
<i>D. Migration</i>						
City migration	-0.037*** (0.002)	-0.024*** (0.001)	-0.037*** (0.002)	-0.024*** (0.001)	-0.037*** (0.002)	-0.024*** (0.001)
Live in metro area	0.019*** (0.001)	-0.008*** (0.001)	0.015*** (0.001)	-0.009** (0.001)	0.020*** (0.001)	-0.008** (0.001)
<i>E. Health and behaviour</i>						
Teenage parenthood	-0.008*** (0.001)	0.003*** (0.001)	-0.009*** (0.001)	0.002*** (0.001)	-0.009*** (0.001)	0.002*** (0.003)
Observations	22,767,599	22,767,599	22,767,599	22,767,599	22,767,599	22,767,599

Note: 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. Columns 1 and 2 report coefficients using our baseline treatment definition (mothers in the top 25% of the predicted-probabilities distribution), while columns 3–6 report coefficients for alternative definitions for treatment. A detailed description of outcomes used as dependent variables is given in Appendix Table A1. (* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$).