Cash and Cognition: The Impact of Transfer Timing on Standardized Test Performance and Human Capital*

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Abstract

This paper shows that the timing of cash transfers to low-income families affects students' cognitive performance on high-stakes standardized tests and subsequent life trajectories. We combine administrative records from the world's largest conditional cash transfer program with college admission exam results of 185,000 high school students from beneficiary families. Exploiting random variation in payment dates, we find that receiving the transfer in the days preceding the exam increases test scores relative to receiving it the subsequent week. Question-level analysis reveals that effects are concentrated in easier questions and questions toward the end of the exam, consistent with increased cognitive bandwidth and endurance. The impacts are largest for the poorest recipients, who experience gains in human capital accumulation: they are more likely to enroll in college and to have completed a college degree seven years after taking the exam. These educational gains translate into improved labor market outcomes, with higher formal employment rates nine years after the exam. Our findings show that short-term liquidity constraints during high-stakes events can have long-lasting consequences, and suggest opportunities to improve social programs through better payment scheduling.

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1 Introduction

Cash transfer programs are among the most prominent anti-poverty policies in developing countries, reaching hundreds of millions of households globally (Banerjee et al., 2024). In Latin America alone, 18 countries operate such programs, covering over 135 million individuals (Garcia and Saavedra, 2022). Given the scale and central role of cash transfer programs in social protection, understanding how to optimize their effectiveness could benefit millions of households.

In this paper, we examine the potential of payment timing around high-stakes academic exams to shape beneficiaries' life trajectories. We begin by testing whether the arrival of a cash transfer shortly before the exam boosts beneficiary students' short-term cognitive performance, enabling them to achieve higher test scores. We then follow these students for nearly a decade to assess whether the score gains translate into lasting impacts on human capital accumulation—such as higher college enrollment and graduation—and early-career labor market outcomes, including formal-sector employment.

We study Brazil's *Bolsa Familia Program* (BFP)—the world's largest conditional cash transfer (CCT) program by coverage, which serves over 13 million households. BFP provides monthly transfers to low-income households, granting on average $94 per month, which represents approximately 50 percent of beneficiaries' monthly income. To measure cognition, we combine BFP administrative records with data from 185,000 high school students from beneficiary families who took a multiple-choice high-stakes exam used for college admissions called ENEM.

Our identification strategy exploits exogenous variation in payment dates. The day of the month a household receives its BFP payment is determined by the last digit of a randomly-generated beneficiary identifier. In our sample, approximately 60 percent of households receive their monthly BFP transfer before the ENEM exam ("early recipient"), while the remainder receive it the week after the exam ("late recipient"). Over 90 percent of early recipients withdraw their benefits prior to the ENEM exam, creating as-good-as-random variation in household liquidity at the time of the exam.

Our main result is that receiving the transfer before the exam improves cognitive performance. Early recipients score approximately one percent of a standard deviation higher than late recipients. We find positive effects across all exam subjects, with the largest effects in language arts and the essay. The effects are concentrated in the middle of the score distribution and are driven by large-transfer recipients—those in the top third of transfer

size—with limited effects for recipients of smaller transfers. Large-transfer recipients have lower income and depend more heavily on BFP transfers, indicating that the cognitive effects are particularly pronounced for the most vulnerable households. Early transfer receipt boosts performance on the easier questions that are within students' reach, but has no effect on the most challenging questions that far exceed their ability. Importantly, these effects are not driven by changes in test-taker composition, as early recipients have the same probability of attending the exam as late recipients.

To investigate mechanisms, we analyze heterogeneity along two dimensions. First, we exploit variation in the number of days between transfer receipt and the exam. If early receipt primarily enables preparatory investments—such as sustained improvements in nutrition or study time—we would expect larger effects the earlier the transfer arrives. Instead, we find a flat profile within the early-receipt window, suggesting that the relevant channels operate quickly, such as alleviating acute material needs or reducing day-of-exam stress.

Second, we leverage question-level data to examine whether transfer timing affects students' ability to sustain performance as cognitive fatigue accumulates during the exam. We exploit the random assignment of test booklets to students, where all booklets have the same set of questions but in different positions. This allows us to study how students perform on a given question when encountering it early in the exam versus in a later position, after accumulated cognitive fatigue. We find that the effects of early transfer receipt are concentrated in the final questions of the exam, consistent with increased cognitive endurance (Mani et al., 2013; Sievertsen et al., 2016; Reyes, 2023; Brown et al., 2024).

Our analysis traces the educational trajectories of test-takers for seven years after the exam, allowing us to test whether cash transfer timing around the ENEM exam leads to persistent gains in human capital accumulation. The ENEM plays a central role in Brazil's higher education system, determining access to scholarships, student loans, and university admissions for over five million test-takers annually (Machado and Szerman, 2021). Given the exam's scale, even modest increases in ENEM scores could significantly affect students' college trajectories. To examine effects on college outcomes, we link ENEM records to Brazil's higher education census, focusing on large-transfer recipients—the group where we found effects on test scores.

We find that early transfer payments have positive effects on human capital accumulation. Among large-transfer recipients, the college attendance rate increases by 0.7 percentage points (or 4.5 percent relative to a baseline of 15.7 percent). We provide sug-

gestive evidence that increased access to scholarships explains the higher enrollment rates, as early recipients in this group are more likely to cross key score thresholds that determine scholarship allocation. Importantly, those induced to enroll succeed academically: students who received the transfer before the exam are 0.8 percentage points (or six percent relative to a baseline of 13 percent) more likely to hold a college degree seven years later.

Finally, we show that taking the test after having received the transfer improves labor market outcomes. To assess this, we link ENEM test-takers to employer-employee matched data covering the universe of Brazil's formal-sector workers. We observe labor market outcomes for up to nine years after the ENEM exam, allowing us to capture early-career outcomes. For large-transfer recipients, early payment increases the likelihood of having a formal-sector job by one percentage point (or 1.7 percent relative to late recipients). We find no significant effects on earnings or wages during this period, though this null effect may reflect that many students are still completing their degrees or are early in their career trajectories.

Our results demonstrate that liquidity constraints, even if short-lived, can have persistent effects when they coincide with high-stakes events such as college entrance exams. Moreover, the concentration of effects among the most vulnerable students suggests that the magnitude of liquidity relief mediates the cognitive impacts on the exam—and by extension on outcomes later in life. Our findings point to a low-cost opportunity to improve the effectiveness of cash transfer programs through optimized payment timing. Beneficiaries' outcomes can be improved outcomes by aligning transfer schedules with key events in beneficiaries' lives, without requiring changes to benefit levels or eligibility criteria.

This paper contributes to the literature on the design of cash transfer programs. Previous work has analyzed the impact of conditioning transfers on household behaviors, of "labeling" the intended use of benefits, and compared in-kind to cash modalities (e.g., Baird et al., 2011; Cunha, 2014; Attanasio et al., 2015; Benhassine et al., 2015; Cunha et al., 2019). The *timing* of transfers has received less attention as a design feature, even though evidence from social programs in high-income settings suggests that payment timing can substantially affect household behavior.[1] For example, beneficiaries of the U.S. Supplemental Nutrition Assistance Program (SNAP) experience higher rates of food insecurity and lower caloric intake at the end of their monthly disbursement cycle compared to the beginning (Shapiro, 2005; Kuhn, 2018), and subsequent work has linked these caloric

[1]Notable exceptions that study transfer timing in developing countries are Barrera-Osorio et al. (2011), Bazzi et al. (2015), Kansikas et al. (2023) and Angelucci et al. (2024).

cycles to cognitive performance on high-stakes exams (Bond et al., 2022). We provide the first evidence from a developing country showing that cash transfer timing around high-stakes exams can impact longer-run outcomes like college attendance and graduation, offering insights into how improved scheduling can enhance human capital accumulation and labor-market outcomes.

We also contribute to the literature on income shocks and cognitive performance. Recent empirical work shows that poverty can directly impair cognitive functioning (Mani et al., 2013; Schilbach et al., 2016; Dean et al., 2019), that income shocks affect performance on cognitive tests (Lichand and Mani, 2020; Kansikas et al., 2023), and that financial concerns impact task performance (Duquennois, 2022; Kaur et al., 2025).[2]

We advance this literature in four ways. First, we study an existing nationwide policy, which provides both direct policy relevance and substantial statistical power: the income shock we examine reflects actual benefit levels, and our sample size is substantially larger than that of previous studies. Second, we study performance on a high-stakes standardized test rather than laboratory measures of cognition.[3] Third, rather than focusing on direct transfer recipients, we examine effects on household dependents, for whom cognitive impacts may shape human capital accumulation and subsequent life trajectories. Fourth, we track students for up to nine years post-exam, linking short-term cognitive effects to longer-term economic outcomes. To our knowledge, this is the first evidence connecting immediate cognitive benefits from income timing to long-run human capital accumulation.

Lastly, this paper contributes to the literature on CCTs and educational outcomes (Fiszbein and Schady, 2009; Baird et al., 2014; Millán et al., 2019; Garcia and Saavedra, 2022). Previous work finds positive impacts of CCTs on school enrollment, attendance, and dropout rates (e.g., Glewwe and Kassouf, 2012; García and Saavedra, 2017). However, evidence on CCTs' effects on test scores is mixed (Millán et al., 2019). A key empirical challenge is that CCT benefits are often conditional on school attendance, which changes the composition of test takers (Garcia and Saavedra, 2022). Most existing work thus relies on strong identification assumptions to address selection into test-taking (Behrman et al., 2000; Garcia and Hill, 2010; Báez and Camacho, 2011). We circumvent this challenge by exploiting variation in *when* households receive their transfer, which allows us to measure

[2]Other work does not find impacts of income shocks on cognition (Carvalho et al., 2016; Fehr et al., 2022).

[3]Incentives are important for measuring cognitive performance because in their absence, cognitive tests capture not only cognitive ability but also other performance determinants such as intrinsic motivation (Wise and DeMars, 2005; Duckworth et al., 2011; Segal, 2012; Finn, 2015; Gneezy et al., 2019).

impacts on test scores under weaker identification assumptions.[4] We also show that these test score effects translate into meaningful differences in college enrollment and graduation.

2 Institutional Context and Data

2.1 Cash Transfer Program

The *Bolsa Família Program* (BFP) is a conditional cash transfer (CCT) program that provides monthly benefits to low-income families in Brazil. BFP covers about 14 million households, reaching over 50 million individuals (approximately 25 percent of the country's population), making it the largest CCT program worldwide (Brollo et al., 2020).

BFP benefits are determined by household composition and income through a two-tier structure. Households below the extreme poverty line receive both an unconditional transfer and conditional payments tied to children's school attendance and health check-ups. Households between the extreme poverty and poverty lines are eligible only for the conditional component. In 2013, the year we analyze, the average beneficiary family received a monthly payment of $94, representing approximately half of their average monthly income of $197.

To enroll in BFP, households must register in the Social Programs Registry (*Cadastro Único*). During registration, each household is assigned a randomly generated eleven-digit identification number called *NIS*. The disbursement schedule of the benefits each month is directly linked to the last digit of the NIS number. Households whose NIS ends with the digit '1' are the first ones to receive the transfer, typically on the third Monday of the month. Thereafter, transfers are made sequentially, with each subsequent day serving those whose NIS ends with the next sequential digit, and with no disbursements occurring over the weekends and public holidays. This staggered payment schedule spans the last 10 to 14 days of each month.

Figure 1 illustrates the October 2013 payment schedule and reveals a unique feature of that year: the ENEM exam fell in the middle of the disbursement period, with some households receiving their transfer before the exam and others after. This timing created exogenous variation in liquidity at the time of the test, as payment dates are determined solely by the randomly assigned NIS last digit. Our identification strategy, described in

[4]By focusing on immediate effects, our design rules out many indirect channels through which cash transfers can impact cognition. For instance, one of the conditions to remain enrolled in BFP is for school-age children to be enrolled in school and attend. Thus, BFP could have long-term impacts on cognition partly due to their impact on schooling (Hansen et al., 2004; Brown et al., 2024).

Section 3, exploits this variation to estimate the causal effect of transfer timing on test scores.

2.2 ENEM Exam

The High School Assessment Exam (*Exame Nacional do Ensino Médio*, or ENEM) is a high-stakes exam that plays a central role in Brazil's higher education system. Most selective universities in Brazil, including those in the centralized admission system, use ENEM scores as their sole admission criterion. Application components common in other countries, such as extracurricular activities, interviews, or motivation essays, play no role in these institutions. ENEM scores also determine eligibility for government scholarships through ProUni (*Programa Universidade para Todos*) and student loans through FIES (*Fundo de Financiamento ao Estudante do Ensino Superior*).

The ENEM exam consists of an essay and 180 multiple-choice questions across four subjects: mathematics, natural sciences, social sciences, and language arts. Each exam subject is graded based on Item Response Theory (IRT). Testing occurs once a year over two consecutive weekend days. Test-takers are randomly assigned an exam booklet that contains the same set of questions but in different orders within each subject area.

2.3 Data

We combine several administrative datasets inside secured room facilities located in Brazil that are managed by the Ministry of Education. Our primary dataset consists of the 2013 ENEM exam records, which contain both student- and question-level information. The student-level data include test scores and demographic characteristics such as age, gender, race, and self-reported family income. The question-level data provide information about the subject and skill being tested as well as the position of each question in the booklet.

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To identify students from BFP recipient households, we link the ENEM records to the Registry of Social Programs and BFP payment sheets from 2013. These datasets contain information on households receiving BFP, including transfer size, withdrawal dates, and

beneficiaries' NIS numbers, which determine the day households receive their monthly transfer.

To examine longer-run outcomes, we link these records to two additional datasets. The Census of Higher Education (2014-2021) provides information on college enrollment, field of study, degree progress, and graduation outcomes. The RAIS employee-employer matched data (2014-2022) contains earnings, occupation, and industry information for all formal-sector workers in Brazil.

2.4 Sample, Summary Statistics, and Balance

To construct our sample, we focus on high school seniors from BFP recipient households who enrolled to take the 2013 ENEM. We implement several sample restrictions. First, we exclude students whose families are not enrolled in BFP. Second, we exclude a small fraction of students from households that were enrolled in BFP but did not receive transfers during the exam month, typically due to ineligibility or non-compliance with program requirements. Third, we exclude individuals who take the exam in their junior year, as these students typically do so for practice. Fourth, we exclude individuals who take the exam after dropping out of high school, who typically take the ENEM to obtain a high school equivalency certificate. Fifth, we exclude individuals who take the exam after graduating from high school, who often take the exam to enroll in a college degree or switch between college degrees. To ensure we capture potential new entrants into higher education, we also exclude students who appear in the higher education census as enrolled in college during or prior to taking the ENEM exam. These restrictions yield a sample of approximately 185,000 students.

Table 1 presents summary statistics for our sample and comparison groups. Column 1 shows characteristics of all high school seniors who registered for the ENEM exam, while columns 2–3 and 4–5 compare students by their enrollment status in the Social Programs Registry and BFP, respectively. Our analysis sample, shown in column 4, consists of students who are older (20.5 years versus 18.9 among all high school seniors), more likely to be female (65.2 percent versus 58.8 percent among all seniors), and more likely to identify as Black or Brown (72.4 percent versus 53.5 percent among all seniors). Students in our sample come from disadvantaged backgrounds, with only 1.8 percent attending private high school (compared to 18.6 percent of all high school seniors) and 2.0 percent having college-educated mothers (compared to 16.2 percent among all seniors). Among test-takers, BFP beneficiaries score approximately 0.6 standard deviations below non-beneficiaries across all

exam subjects.

The sample is balanced on observable characteristics across payment timing groups. Table 2 compares mean characteristics of students whose households receive BFP transfers before versus after the 2013 ENEM exam (columns 1 and 2). Out of twenty covariates tested, we can only reject equality for one variable (disbursement of benefits through bank deposit). Even then, the difference is economically small, with a standardized difference of 0.009 SD (column 4). We also find a balanced sample when examining student characteristics across all ten possible NIS last digits (Appendix Table A1). Consistent with random assignment, the last digit of household NIS numbers is uniformly distributed across students (Appendix Figure A1).

3 Research Design

3.1 Regression Model

Our empirical strategy exploits random variation in the timing of BFP transfers relative to the ENEM exam. Households' randomly-assigned NIS numbers determine their payment date each month, with the 2013 ENEM exam falling in the middle of the disbursement period. We use this variation to estimate the following baseline specification:

$$Y_i = \alpha + \beta \text{EarlyTransfer}_i + \varepsilon_i, \tag{1}$$

where Y_i denotes student i's outcome and EarlyTransfer_i equals one if student i's household receives its transfer before the exam (NIS last digits 1–6), and equals zero otherwise (digits 7–0). We cluster standard errors at the student level to account for the small number of students who appear in multiple BFP-beneficiary households.

The coefficient β measures the causal effect of having access to BFP funds before versus after the exam. We interpret this parameter as the effect of alleviating end-of-cycle financial constraints—the liquidity shortages that households may face in the days before their next transfer payment. Rejecting the null hypothesis that $\beta = 0$ would provide evidence that households face binding end-of-cycle constraints that affect cognitive performance.

3.2 Main Outcomes

We examine three categories of outcomes (see Appendix C.1 for variable definitions). Our primary outcome is test performance (see Appendix D for a conceptual framework that

connects cash transfers to cognitive functions and test performance). We use the IRT-based scores provided by the testing agency, standardized to have mean zero and standard deviation one in our sample. We analyze both overall performance—measured as the average IRT score across all subjects—and subject-specific performance in mathematics, natural sciences, social sciences, language arts, and the essay. To examine where effects concentrate in the score distribution, we also estimate specifications using indicators for scoring above various thresholds. To investigate mechanisms, we leverage question-level data to analyze how performance on individual questions varies with their position in the exam and difficulty level.

To assess longer-run impacts, we examine college and labor market outcomes. For college outcomes, we track students for seven years following the ENEM exam. We measure college enrollment (appearing in the higher education census one year post-ENEM), college quality (based on graduates' mean earnings from administrative data), persistence (remaining enrolled through years one to three), and degree completion (graduating within seven years).

For labor market outcomes, we observe students for up to nine years after taking the exam. We examine formal-sector employment (appearing in employer-employee matched data), monthly earnings, and hourly wages. All monetary values are inflation-adjusted and expressed in 2023 U.S. dollars.

3.3 Transfer Payment Timing and Withdrawal Patterns

As a first step toward understanding the impact of payment schedules, we use BFP payroll data to examine when households withdraw their benefits relative to BFP disbursement dates.[5] Figure 2 plots the cumulative distribution function (CDF) of withdrawals relative to scheduled payment dates. Since payment dates vary across households based on their NIS number, we normalize the timeline so that each household's payment date equals zero. The x-axis represents days relative to the payment date, while the y-axis shows the cumulative share of households that have withdrawn their benefits.

Withdrawal patterns are consistent with binding liquidity constraints and households' need for immediate access to funds. We observe virtually no withdrawal activity before the scheduled payment date. On the payment date itself, approximately 75 percent of

[5]Withdrawals must be made for the full monthly benefit amount; partial withdrawals are not permitted. The benefit can be accessed at Caixa offices, lottery offices, authorized bank branches, automatic teller machines, and post offices. It needs to be withdrawn within 90 days.

households withdraw their benefits, and this share rises to over 85 percent within three days. This rapid withdrawal behavior means that the vast majority of households scheduled to receive transfers before the exam had accessed their funds prior to the exam weekend (Appendix Figure A2).

4 The Impact of Monetary Transfers on Exam Performance

This section examines how the timing of BFP transfers affects students' exam performance. We first assess whether receiving transfers before the exam influences likelihood of attending the ENEM. We then present our main results on test scores, examining both overall performance and subject-specific effects. Finally, we explore heterogeneous effects by transfer size and student characteristics.

4.1 Exam Attendance

The timing of transfer receipt could influence exam attendance patterns. If receiving transfers systematically affects the attendance decisions of higher- or lower-ability students, this selective attendance could generate spurious test score differences between early and late recipients that are unrelated to cognitive effects. To examine this possibility, Table 3 reports estimates from equation (1) with attendance as the dependent variable. We consider multiple attendance measures: whether students attended both exam days, at least one day, and each day individually. Appendix Figure A3 complements these results by plotting attendance rates as a function of days elapsed since transfer receipt.

We find no evidence that transfer timing affects exam attendance. Early recipients are 0.1 percentage points less likely to attend both days (on a baseline of 75.8 percent) and 0.2 percentage points less likely to attend at least one day (on a baseline of 78.5 percent). Both effects are economically small and statistically insignificant, with similar null results for first-day and second-day attendance (columns 3 and 4). Appendix Figure A3 confirms that attendance rates do not systematically vary with the timing of household transfer receipt. To further probe potential selection effects, in Appendix Table A2 we estimate an augmented version equation (1) that includes baseline covariates and their interaction with the treatment indicator. We find no evidence of differential selection on observables.

4.2 Test Scores

We now examine how payment timing affects test performance. Table 4 presents estimates of $\hat{\beta}$ from equation (1). Column 1 reports results for the average score across all subjects, while columns 2–6 present estimates separately for each multiple-choice subject and the essay. For visual evidence of these effects, Figure 3 plots mean test scores for early and late recipients by subject.

Receiving the cash transfer in the days preceding the exam improves test scores. On average, receiving BFP early improves test scores by $\hat{\beta} = 0.009$ SD ($p < 0.05$), as shown in column 1. We find positive effects across all subjects (columns 2–6) and essay components (Appendix Table A9, Panel A). The effect is larger for language arts ($\hat{\beta} = 0.014$ SD, $p < 0.01$) and the essay ($\hat{\beta} = 0.010$, $p < 0.10$). While we estimate positive impacts on the sciences and math, these effects are not statistically significant. The essay improvements are particularly large for language proficiency—which assesses mastery of formal written Portuguese including grammar, spelling, and syntax—and for coherence and cohesion, which evaluates logical sequencing of ideas and use of transitional devices. These results are robust to controlling for socioeconomic and demographic characteristics (Appendix Table A3).

To understand where in the score distribution these effects concentrate, we examine how transfer timing affects the probability of exceeding various score thresholds. Figure 4 presents estimates of equation (1) using indicators for surpassing different score cutoffs as outcomes, with scores measured on the original ENEM scale (mean 500, standard deviation 100). The effects concentrate in the middle of the distribution: early recipients are significantly more likely to score above thresholds between 400 and 500 points, with peak effects around the 450-point range. However, transfer timing has no impact on the likelihood of achieving scores above 550 or below 350.

To understand what types of questions drive these test score improvements, we examine whether effects vary by question difficulty. The ENEM is a challenging exam; students in our sample answer only 27 percent of questions correctly on average. We might therefore expect score improvements to concentrate on questions within students' reach rather than those far exceeding their preparation. To assess this, we classify questions into difficulty quintiles based on the share of incorrect responses among non-BFP test-takers and estimate equation (1) separately for each quintile. Figure 5 presents these estimates. The benefits of early transfer receipt concentrate on relatively easier questions. Early recipients are 0.19 percentage points more likely to answer questions in the easiest quintile correctly

($p < 0.05$), and the effects decline monotonically as difficulty increases. For the most difficult quintiles, treatment effects are indistinguishable from zero.

Our estimates indicate that early receipt of BFP improves exam performance by approximately one percent of a standard deviation. This effect is consistent with the distribution of effect sizes found in education interventions in low- and middle-income countries, where the 25th percentile of learning impacts from RCTs is 0.01 SDs (Evans and Yuan, 2022). This effect is comparable to increasing teacher value-added for one school year by 0.06 standard deviations (Chetty et al., 2014a), reducing air pollution during testing by 0.20 standard deviations (Ebenstein et al., 2016), lowering ambient pollen levels by 0.32 standard deviations (Bensnes, 2016), or decreasing testing room temperature by one degree Fahrenheit (Park, 2020).[6]

4.3 Threats to Identification

We address two potential threats to identification. First, other government programs might distribute benefits based on NIS digits, potentially confounding our estimates if their payment schedules align with BFP transfers. To test this, we examine a placebo group: students from households enrolled in the Social Registry who do not receive BFP.[7] This placebo test isolates any effects from non-BFP programs that might use NIS-based payment timing. Appendix Table A10 shows that effects for this group are economically small and statistically insignificant, confirming that our results are driven by BFP transfers specifically.[8]

Second, our estimates might reflect cumulative effects of consistent monthly payment timing rather than short-term liquidity variation. For example, households whose payment date aligns more closely with large monthly expenses may be better able to manage resources, with potential cumulative benefits for children's development. To address this concern, we leverage information on the exact date each household first enrolled in the

[6] Another way to benchmark our effect size is to estimate the public funds required to achieve a comparable test score increase. In a meta-analysis of public school spending impacts, Jackson and Mackevicius (2023) finds that increasing spending by $1,000 per student for four years leads to a test-score increase of 0.031 SD. Extrapolating this U.S.-based estimate to Brazil and assuming that the impact of public funds scales linearly, our estimated increase of 0.009 SD (Table 4, column 1) would require approximately $260 per student for four years (or about $115 million, given the number of students who are early-recipients).

[7] As detailed in Section 3, households obtain an NIS identifier upon enrolling in the Social Registry, which is required for all government benefits, not just BFP.

[8] This finding aligns with information from Ministry of Social Development staff—the ministry in charge of managing BFP—who confirmed that no other programs used NIS digits to determine payment schedules during this period.

social programs registry. We estimate equation (1) controlling for the number of months the household has been enrolled in the social programs registry.[9] Appendix Table A11 shows that our estimates remain virtually unchanged, indicating that our research design captures the impact of short-term liquidity differences, rather than cumulative benefits of payment timing.

4.4 Heterogeneous Treatment Effects

Understanding which households and students benefit most from transfer timing is crucial for program design and targeting. We examine heterogeneity using two complementary approaches. First, we analyze treatment effects across specific student characteristics by estimating augmented versions of equation (1) that include both the characteristic and its interaction with early transfer receipt.

Second, we employ causal forest methods (Wager and Athey, 2018) to identify patterns of heterogeneity in a data-driven manner. The causal forest estimates conditional average treatment effects (CATEs) for each student using all available characteristics from the ENEM and BFP administrative records. To identify which variables drive heterogeneity, we compute "variable importance" measures following Athey et al. (2019), which capture the proportion of splits using each covariate across all trees in the forest.

4.4.1 Student Characteristics. Appendix Tables A12 and A13 present heterogeneous effects by student characteristics and household composition. We find significant heterogeneity only by maternal education. Students with college-educated mothers experience effects that are 0.057 SD larger than those whose mothers lack college degrees ($p < 0.10$, column 1). This pattern may reflect higher perceived returns to education among college-educated mothers (Boneva and Rauh, 2018), who may direct more transfer resources toward educational investments.[10] Other student characteristics show no significant heterogeneity. Effects are similar for full-time working students versus other students, females versus males, and for white versus non-white students (columns 3–4). Household composition—including household size and number of children—also does not moderate treatment effects.

[9] While registry enrollment dates may not perfectly correspond to BFP enrollment dates, both dates are likely highly correlated.

[10] We interpret this finding cautiously, as only two percent of test-takers have college-educated mothers. Among this subgroup, BFP-eligible households are likely highly selected.

4.4.2 Causal Forests. Appendix Table A8 ranks variables by their importance in predicting heterogeneous effects, measured as the proportion of splits using each covariate across all trees in the forest. The top predictors include household income (0.169), share of income from BFP (0.134), age of household head (0.092), number of income earners (0.082), and total transfer size (0.072). These economic and household head characteristics substantially outrank demographic variables in predictive importance. Household composition shows limited relevance: household size (0.031), presence of young children (0.025), and number of teenagers (0.016) account for few splits. Student characteristics—including gender (0.009) and work status (0.006)—are similarly unimportant. This pattern suggests that household economic characteristics, rather than demographic composition or student attributes, are the primary drivers of heterogeneous treatment effects. We next examine this relationship between household economic conditions and treatment effects more systematically.

5 Financial Strain and Effect Size

Evidence from multiple contexts demonstrates that cognitive responses to income shocks concentrate among the most financially constrained. Kaur et al. (2025) find that cash infusions improved productivity and attentiveness only among low-wealth workers in India. Duquennois and Jagnani (2025) document a similar pattern in Indonesia, where cash transfers improved sleep quality primarily for heavily indebted households. Most relevant to our setting, Lichand and Mani (2020) show that cognitive performance among BFP recipients declines before transfer receipt, but only in Brazil's poorest municipalities.[11] Consistent with this literature, our causal forest analysis identifies economic variables as the primary drivers of heterogeneity: four of the five most important predictors—household income, share of income from BFP, total transfer size, and number of income earners—directly measure financial strain.

These findings suggest that transfer timing should matter most for households experiencing the greatest financial strain—those most likely to exhaust resources before month's end. We test this hypothesis by examining whether the impact is larger for households who receive larger transfers, which captures both household dependence on BFP income

[11]The importance of baseline financial strain may explain conflicting findings in the literature: while Carvalho et al. (2016) find no cognitive effects of payday timing in their U.S. sample, Farbmacher et al. (2021)'s reanalysis reveals significant effects among the most financially strained subgroup.

and baseline poverty, and verify robustness to alternative proxies of financial strain.[12] We leverage the substantial variation in transfer amounts in our sample: while the average household receives $94 monthly, the standard deviation is $49. Following Gelman and Park (2009), we divide students into terciles based on their household's monthly benefit amount. The bottom, middle, and top terciles receive average monthly transfers of $51, $92, and $175, respectively. Households in the top tercile depend more heavily on BFP income—they are larger, have lower per capita income, and rely on transfers for a greater share of their total resources (Appendix Table A4).

5.1 Treatment Effect by Transfer Size Tercile

Test score effects concentrate among the most financially strained households. Table 5 presents estimates of equation (1) separately by tercile. For students in the top tercile of transfer size (henceforth "large-transfer recipients"), early payment improves average test scores by $\hat{\beta} = 0.02$ SD ($p < 0.01$), as shown in Panel A, column 1. Both Kolmogorov-Smirnov and Wilcoxon rank-sum tests reject equality of score distributions between early and late recipients ($p < 0.10$ and $p < 0.01$, respectively). The effects are positive across all subjects, with the largest gains in language arts ($\hat{\beta} = 0.026$ SD, $p < 0.05$) and the essay ($\hat{\beta} = 0.025$ SD, $p < 0.05$).[13] The performance gains for large-transfer recipients are broadly distributed across the score range. Appendix Figure A5 shows that early recipients are more likely to exceed score thresholds throughout the distribution, with peak effects occurring between 400 and 520 points on the original ENEM scale—spanning the 20th to 90th percentiles. Performance improvements are driven by the relatively easier questions. Early recipients are 0.57 percentage points more likely to answer questions in the easiest quintile correctly ($p < 0.01$), and the effects decline monotonically with difficulty (Appendix Figure A6).

In contrast, we find no effects among less financially strained households. Students in the middle and bottom terciles show smaller, statistically insignificant effects (Panels B and

[12] We use transfer size, rather than reported household income, as the primary dimension of heterogeneity. Eligibility for BFP is based on income, and the relevant cutoffs are publicly known, which creates strong incentives for misreporting. Indeed, prior work documents and models such manipulation in BFP directly (Bergstrom et al., 2025), and we later present evidence consistent with manipulation. Moreover, household income is also endogenous to program participation, making transfer size a more reliable proxy for baseline financial strain.

[13] For essay components, the effects are larger for theme development—which evaluates comprehension of the essay prompt, adherence to the assigned topic, and integration of relevant disciplinary knowledge—and coherence and cohesion, which measures logical sequencing of ideas (Appendix Table A9, Panel B).

C), with the difference between the top tercile and bottom two terciles being statistically significant ($p = 0.06$, Panel D). These patterns persist after controlling for demographic characteristics (Appendix Table A5) and are robust to alternative measures of financial strain, including household income (Appendix Table A6) and the share of monthly income from BFP transfers (Appendix Table A7).

5.2 The Causal Effect of Transfer Size on Cognition

The concentration of effects among large-transfer recipients raises the possibility of a positive causal relationship between the magnitude of transfers and their cognitive effects. However, transfer size is confounded by household characteristics—larger and poorer households receive larger transfers by program design. To isolate the causal effect of transfer size, we implement a "difference-in-discontinuities" ("Diff-in-Disc") design that combines eligibility-driven variation in benefit amounts with our random variation in payment timing. We summarize the key insights from this exercise below, and relegate a detailed description of this anaylysis to Appendix B.

Our empirical strategy exploits the sharp increase in benefits at the extreme-poverty threshold. As described in Section 2, households with per-capita income below this cutoff receive an unconditional "basic benefit" of R$70 ($43), a 46 percent increase relative to the mean transfer. This rule induces a discontinuous jump in transfer size that depends only on income relative to the threshold.[14]

In a standard fuzzy Regression Discontinuity (RD), this discontinuity could serve as an instrument for transfer size, under the assumption that households cannot precisely manipulate reported income at the cutoff and that potential outcomes are continuous at c. As we show, we find evidence consistent with manipulation around the threshold, including covariate imbalances (Table B1). We therefore adopt an alternative strategy that relaxes this assumption.

Rather than comparing students just below versus just above the cutoff, we compare the *discontinuities* at the cutoff c for students whose household received the transfer *before* the exam versus *after* the exam. Any discontinuity at c that is common to both groups (including manipulation of reported income) is differenced out. This "difference-in-discontinuities" design ("Diff-in-Disc") identifies whether the causal effect of the additional

[14]This variation has been used by Gerard et al. (2024) to study formal labor supply responses among BFP households and by Bergstrom et al. (2025) to quantify welfare effects of BFP reforms.

R$70 transfer is larger for early recipients than for late recipients.[15] We expect the impact of the additional R$70 to be larger for early recipients, as this group has access to the funds when taking the exam. In contrast, late recipients face the exam while still liquidity-constrained—the additional R$70 arrives only after the test.[16]

Our design generates a discontinuity in transfer size of equal magnitude among early and late recipients: crossing the cutoff increases per-capita transfer size by 17% in both groups (Table B2). However, this marginal increase has cognitive benefits only for those who receive the transfer before the exam. While we obtain a positive RD estimate on exam performance of 0.014 SD among early recipients, we find no discontinuity for the late recipients, with an estimate of −0.004 SD. This yields a Diff-in-Disc estimate on exam performance of 0.018 SD. This estimate is not statistically significant at conventional levels, likely due to the lower power of the DiDisc research design.

Despite being noisily estimated, the positive Diff-in-Disc estimate provides suggestive evidence that the additional basic benefit improves exam performance when households have access to it before the exam. This result aligns with the earlier heterogeneity analysis, which showed stronger effects among larger-transfer recipients, and indicates that part of this heterogeneity reflects the causal impact of transfer size rather than purely endogenous differences across households.

6 Mechanisms Behind Test Score Improvements

What explains the impact of cash transfer timing on test scores? One set of explanations centers on behavioral responses: households might use the funds to address immediate material needs—purchasing higher-quality foods, paying for transportation to the exam venue, or reducing work hours in the days before the exam to increase study time or rest (Beegle et al., 2006; Bond et al., 2022; Duquennois and Jagnani, 2025). Another set involves cognitive mechanisms: receiving transfers before the exam might alleviate acute financial stress, improving cognitive bandwidth and enabling better focus during the test (Mani et al., 2013; Duquennois, 2022; Brown et al., 2024; Kaur et al., 2025).

To shed light on these potential mechanisms, we employ two complementary empirical

[15] Our design is similar in spirit to the difference-in-discontinuities design of Grembi et al. (2016), but in our setting "groups" are defined by payment timing rather than time periods.

[16] Note that if households below the threshold can better smooth consumption across the payment cycle due to the additional resources, this would reduce differences between early- and late recipients, biasing against finding an effect. Thus, our diff-in-disc estimate provides a conservative test of whether immediate liquidity affects cognitive performance.

strategies. First, we exploit timing variation to examine whether effects strengthen with longer exposure to the transfer. Second, we leverage rich question-level data to analyze how transfer timing affects performance as cognitive fatigue accumulates throughout the exam. Given that test score effects concentrate among large-transfer recipients, we focus the mechanism analysis on this subgroup.

6.1 Timing of Transfer Receipt

Many mechanisms imply a dose-response relationship: effects should be larger the longer households have had access to the transfer before test day. For example, if early receipt primarily enables households to make preparatory investments—such as purchasing study materials, improving nutrition over several days, or reducing work hours to increase study time—we would expect larger effects when transfers arrive well before the exam. By contrast, for channels that operate over short horizons—like hunger reduction or lower day-of-exam stress—the precise timing within the early-receipt window should matter less.

To assess differential effects by days since transfer receipt, we present visual evidence on the relationship between transfer timing and test performance. Figure 6 plots average ENEM scores against the transfer disbursement date for large-transfer recipients. Consistent with our main results, the figure reveals a substantial discontinuity between early recipients (blue markers) and late recipients (red markers). Notably, within the early-receipt window, test scores remain remarkably flat across payment dates: students whose families received transfers eight days before the exam perform no better than those who received transfers just one day prior.

This flat profile within the early-receipt window is inconsistent with mechanisms whose impacts take time to materialize. The absence of a gradient also aligns with our heterogeneity analysis, where we found no differential effects based on student work status (Section 4.4), suggesting that time reallocation is not a primary channel. Instead, the discontinuity between early and late receipt points to mechanisms that operate immediately, such as reduced financial stress or alleviation of acute material needs on exam day.

6.2 Cognitive Fatigue and Exam Performance

One cognitive mechanism that may be particularly important in our context is *cognitive fatigue*—the depletion of mental resources that results from sustained effort, which impairs executive functions such as attention, memory, and reasoning (Ackerman, 2011). The

ENEM spans ten hours of testing over two consecutive days. This extreme length places substantial demands on students' ability to maintain focus and performance throughout the exam. A growing body of evidence documents that student performance deteriorates over the course of lengthy exams as mental fatigue accumulates (Sievertsen et al., 2016; Borgonovi and Biecek, 2016; Borghans and Schils, 2018), including specifically in the ENEM (Reyes, 2023).

If early transfer receipt mitigates cognitive fatigue—through improved nutrition, better sleep, or reduced financial stress—then performance should deteriorate less steeply over the course of the exam among Early recipients. In other words, while all students may experience declining performance as question position advances, this decline should be attenuated for students who received the transfer before the exam.

A central empirical challenge is isolating the role of question position itself. Later questions may differ systematically in difficulty or other characteristics, so a simple comparison of performance on earlier versus later questions would conflate fatigue with other channels. We address this challenge by exploiting the random allocation of test booklets in the ENEM. While all students answer the same 180 questions, these appear in different order across booklets within each subject area, generating exogenous within-question variation in position. On average, the same question appears 11 positions apart across booklet pairs, with substantial variation that enables our identification strategy (Appendix Figure A4).

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We leverage this variation in a question-fixed-effects specification that compares performance on the same question when it appears later relative to earlier in the exam. We remain agnostic about how late in the exam fatigue effects emerge. Specifically, we construct a binary variable indicating whether a question appears among the last n questions of each exam day, iterating over multiple values of n, and estimate the following equation at the student-question level:

$$\text{Correct}_{ij} = \delta_j + \beta \text{Early}_i + \phi^n \text{LastQuestions}^n_{ij} + \gamma^n (\text{Early}_i \times \text{LastQuestions}_{ij}) + \mu_{ij}, \quad (2)$$

where Correct_{ij} indicates whether student i correctly answered question j, δ_j are question fixed effects, and $\text{LastQuestions}_{ij}^n$ indicates whether question j appears among the last n questions of either test day. We cluster standard errors at the student level.

The parameter ϕ^n captures the performance gradient associated with late exam position among Late recipients—that is, how much the probability of answering a given question correctly declines when that same question appears among the last n questions of the test day. A negative ϕ^n reflects cognitive fatigue. The interaction parameter γ^n tests whether this decline is attenuated among Early recipients. A positive γ^n implies that Early receipt buffers against the negative effect of late question position.

Figure 7 Panel A documents a substantial fatigue effect among Late recipients. The red bars plot the coefficients on ϕ^n. As a question's position shifts toward the final stages of the test day, the probability of a correct answer declines. This effect is largest when a question appears among the very last positions, ranging from a 1 percentage point reduction in the likelihood of a correct answer for the final question of the day to a 0.5 percentage point reduction for questions appearing among the final five positions.

Crucially, we find that this decline is consistently smaller among Early recipients. The blue bars in Panel A plot the fatigue effect among Early recipients,[17] revealing a similar pattern of deterioration toward the end of the exam, but with a flatter gradient. Panel B directly plots the interaction coefficients γ^n. The fatigue-buffering effect of Early receipt peaks among the last three questions of the test day, where the decline in performance is 0.5 to 0.4 percentage points smaller relative to Late recipients. This differential gradually diminishes as questions appear earlier in the day.

One concern is that these patterns reflect differences in time management rather than fatigue. For instance, Early recipients may be less likely to run out of time, mechanically improving performance on the final questions.[18] To assess this possibility, we restrict the sample to students who answer all questions, for whom time exhaustion is unlikely to drive the results. Figure A7 shows that the fatigue gradient and its attenuation among Early recipients remain virtually unchanged.

Our findings are mutually consistent with a cognitive fatigue mechanism. The flat profile by paydate suggests that the relevant channel operates quickly. This, in turn, is consistent with the pattern documented earlier that treatment effects are concentrated on easier questions: if the mechanism acts immediately, it is unlikely to expand mastery of

[17] This is the sum of ϕ^n and γ^n from equation (2).

[18] An alternative explanation would be that Early recipients become more efficient test-takers, spending less time per question and thus arriving at the final stages with more time remaining.

more difficult material, but by reducing fatigue it may help students sustain attention and avoid the kinds of "careless mistakes" that arise when mental resources are depleted. The fact that effects are strongest at the end of the exam further supports this interpretation, as that is when cognitive fatigue is most pronounced. The convergence of these patterns provides suggestive evidence that alleviating cognitive fatigue is an important channel through which early transfer receipt affects performance.

7 Transfer Timing and Human Capital Accumulation

College attendance in Brazil exhibits a strong test-score gradient, comparable to patterns documented for the SAT and ACT in the U.S. States (Hoxby and Turner, 2013; Chetty et al., 2020; Sacerdote et al., 2025). In our data, a one-point increase in raw ENEM scores is associated with a 0.2 pp increase in college enrollment probability among high school seniors. This relationship reflects both selection—higher-ability students are more likely to attend college—and the institutional role of ENEM scores in determining admissions, scholarships, and financial aid eligibility (Section 2).

Our estimated raw score effect of 1.82 points for large-transfer recipients implies that transfer timing could affect college access through this channel. This section examines whether the test score improvements translate into persistent effects on human capital accumulation. We present results for both the full sample and large-transfer recipients separately, as test score effects concentrate on this subgroup.

7.1 Methodology and Main Outcomes

The higher-education census allows us to observe students' college trajectories up to seven years after they take the ENEM exam. We use this information to define several variables and estimate equation (1) using these variables as outcomes.

We focus on five main outcomes (see Appendix C.1 for detailed variable definitions): *College enrollment* is an indicator for appearing in the higher education census one year after taking the ENEM. We examine overall enrollment as well as enrollment by institution type (public versus private) and field of study (teaching degrees, technical programs, STEM fields, and non-STEM fields). *Earnings potential* captures the expected earnings associated with each students' post-secondary school trajectory, which we measure by leveraging employer-employee matched data to calculate mean earnings for graduates from each uni-

versity following Chetty et al. (2014b).[19] *College persistence* is an indicator for remaining enrolled three years after taking the ENEM exam. *College graduation* is an indicator for completing a degree within seven years of the exam. *Financial assistance* is an indicator for receiving any scholarship support during the first year of enrollment.

7.2 College Enrollment, Earnings Potential, and Graduation

Receiving the cash transfer in the days preceding the exam increases the likelihood of subsequently enrolling in college. For the full sample, receiving BFP before the exam increased college enrollment by $\hat{\beta} = 0.2$ pp, though this estimate is not statistically significant at the usual levels (Table 6, Panel A, column 1). Among large-transfer recipients, early receipt increased enrollment by $\hat{\beta} = 0.7$ pp ($p < 0.10$), which represents a 4.5 percent increase relative to the late-recipients' baseline enrollment rate of 15.7 percent (Panel B, column 1). This magnitude aligns with the cross-sectional test score gradient: given that a one-point increase in raw ENEM scores predicts a 0.2 pp increase in enrollment, our estimated score improvement would predict an enrollment effect of approximately 0.4 percentage points—well within our confidence interval.

To understand where marginal enrollees matriculate, we examine heterogeneity across institution types and fields of study. The enrollment gains concentrate in private institutions and non-STEM programs. Among large-transfer recipients, early payment increases private college enrollment by 0.6 pp while having no significant effect on public college enrollment (Table 6, columns 2–3). The effect on non-STEM degrees is 0.6 pp ($p < 0.15$), accounting for almost the entire enrollment increase (Table A14, column 4). We find smaller and statistically insignificant increases in STEM fields (column 6).

Early transfer receipt also improves students' earnings potential. Large-transfer recipients who received payment before the exam choose post-secondary-school trajectories with $\beta = \$5.4$ higher expected monthly earnings—a 1.2 percent increase relative to late recipients ($p < 0.05$, Table 6, Panel B, column 4).

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The initial enrollment gains translate into sustained improvements in human capital accumulation among large-transfer recipients. Early BFP recipients in this group have a $\beta = 0.8$ pp higher likelihood of being enrolled in college three years after the ENEM ($p < 0.05$), which represents a 4.1 percent increase relative to the late-recipient mean of 19.6 percent (Panel B, column 5). Importantly, seven years after the exam, early transfer

[19] Students who do not enroll in college are assigned the average informal-sector earnings in their state.

recipients are $\beta = 0.8$ percentage points ($p < 0.05$) more likely to have graduated from a university program (Panel B, column 6). The magnitude of these effects aligns with our enrollment findings, suggesting that the marginal students induced to attend college by early transfer receipt succeeded academically. We find no significant effects on persistence or graduation rates in the full sample or among recipients of smaller transfers (Panels A, C, and D).

7.3 Mechanisms for College Access

To understand how higher test scores translate into increased college enrollment, we examine two main channels through which early BFP receipt affects college access.

7.3.1 Admission to Selective Programs. First, we examine whether higher test scores increased admission chances at selective universities. Better scores could mechanically increase admission probabilities if they push students above program admission cutoffs. To assess this, we analyze enrollment patterns at institutions that use ENEM scores for admissions, focusing particularly on public universities where admissions are highly competitive and exclusively determined by ENEM performance. We do not find evidence that increased college enrollment stems from students clearing critical admission thresholds. We find null effects on enrollment at both public colleges (Table 6, column 3), which comprise the majority of institutions that use the ENEM for admissions, and selective colleges that use ENEM scores irrespective of being public or private (Table 7, column 1). These null results are consistent with the highly competitive nature of public university admissions, where cutoff scores substantially exceed the performance of BFP beneficiaries.[20] Since the effects on test scores are concentrated in the middle of the score distribution, these improvements are unlikely to affect admission prospects at selective institutions.

7.3.2 Access to Financial Aid. Why would students be more likely to enroll in open-admission institutions where test scores do not determine admission? One possibility is that higher ENEM scores unlock financial aid opportunities that make college affordable. In Brazil, scholarships and aid programs serve as crucial pathways for low-income students to access private higher education. In our data, 19.3 percent of large-transfer college

[20] Figure A8 illustrates this by comparing public university admission thresholds from the centralized admission system in 2017 (earliest year for which we have access to this data) to the distribution of low-income students' ENEM scores.

enrollees received some form of scholarship, underscoring the importance of financial aid for this population. ENEM scores are central to scholarship programs: they determine eligibility and rank applicants. For example, the federal ProUni program—which provides full and partial tuition scholarships to low-income students at private universities—requires an average ENEM score above 450 points across all subjects and a non-zero essay score.

We first assess whether students are more likely to qualify for merit-based financial aid. Aid is allocated at multiple levels — federal programs, state initiatives, and university-specific scholarships — each with potentially different eligibility thresholds. The Census of Higher Education allows us to back out scholarship cutoffs for all academic programs in the country. Specifically, for each program, we define its scholarship cutoff as the minimum ENEM score among students who enrolled in that program in 2014 (the year immediately following the exam) and received a scholarship.[21]

Using these recovered program-level cutoffs, we construct measures of the financial aid opportunity set available to each student. For every student, we compare their ENEM score to the set of scholarship cutoffs across programs located in their home state.[22] We then compute two outcomes: (i) the number of programs in each student's home state for which their ENEM score exceeds the scholarship cutoff, and (ii) the share of programs for which their ENEM score exceeds the scholarship cutoff.

Early BFP receipt significantly expands students' opportunity set of scholarship-eligible programs. (Table 7, column 2) shows that the number of programs for which a student is scholarship-eligible in their state increases by 12.7, or 4.4% ($p < 0.05$). The share of scholarship-eligible programs in the state also increases accordingly, by 0.6pp (column 2). We find consistent effects when defining scholarship eligbility through an alternative approach described in Appendix C.2 (column 3). Consistent with improved scholarship eligibility, early recipients who enroll in college are 0.8 percentage points (or 4.1 percent) more likely to receive financial aid, though this effect is not statistically significant at the conventional levels (column 3). These results suggest that even modest test score improvements can unlock financial resources that enable college enrollment for low-income students.

[21] Under the institutional rules governing these programs, scholarships are awarded based on ENEM performance and capacity constraints; thus, the lowest-scoring scholarship recipient in a program corresponds to the effective eligibility threshold for that program in that year.

[22] We focus on the state-level higher education market because students rarely leave their home state for college (Machado and Szerman, 2021).

8 Early-Career Labor Market Outcomes

This section examines whether the test score improvements from early transfer receipt generate persistent effects on employment and earnings. We track students for up to nine years after the ENEM exam, capturing early-career outcomes as they transition from education to the labor market. As with college outcomes, we present results for both the full sample and large-transfer recipients separately.

8.1 Labor Market Context

Like in many developing countries, Brazil's labor market is characterized by a sharp divide between formal and informal employment. In 2023, approximately 39 percent of the workforce operated in the informal sector, where workers lack access to mandated benefits including health insurance, paid sick leave, unemployment insurance, and retirement contributions (Haanwinckel and Rodrigo, 2017). Beyond these protections, formal employment tends to offer greater job security, predictable income streams, and clearer paths for career advancement.

Access to formal employment is strongly tied to educational attainment. Given the positive effects on college enrollment and graduation documented in Section 7, early transfer recipients may achieve better labor market outcomes through their increased human capital.

8.2 Methodology and Main Outcomes

The RAIS employer-employee matched dataset allows us to track students' formal-sector employment for up to nine years after they take the ENEM exam. We use these data to construct measures of early-career labor market success and estimate equation (1) with these measures as outcomes.

We examine three outcomes: *Formal employment* indicates whether students appear in RAIS data at any point, capturing successful entry into the formal labor market. *Monthly earnings* measures average inflation-adjusted earnings conditional on employment (2023 USD). *Hourly wages* adjusts for work intensity by dividing monthly earnings by contracted hours. See Appendix C.1 for detailed definitions.

8.3 Employment and Earnings

Early increases the likelihood of formal employment among large-transfer recipients (Table 8, Panel B). Column 1 shows that receiving the transfer before the exam increases the probability of formal employment by 1 percentage point ($p < 0.05$), representing a 1.7 percent increase relative to the late-recipient mean of 59.4 percent. We find no detectable effects on earnings or wages. Early recipients earn $\hat{\beta} = \$1.2$ more per month, an economically small and statistically insignificant difference (column 2). Similarly, hourly wages show a precisely estimated null effect of $\hat{\beta} = \$0.01$ (column 3). These null earnings effects likely reflect several factors: many students in our sample are still completing their degrees during the observation period and others are in entry-level positions early in their career trajectories. Consistent with the lack of effects on college outcomes, we find no detectable effects on labor market outcomes in the full sample (Panel A), or among recipients of smaller transfers (Panels C and D).

9 Discussion

This paper shows that liquidity constraints can have persistent effects on economic mobility when they coincide with high-stakes events. We show that receiving a cash transfer shortly before a college entrance exam improved students' cognitive performance, particularly among recipients of larger transfers. These test score gains translated into meaningful differences in educational attainment, with early recipients more likely to both enroll in and complete college degrees. The improved human capital accumulation ultimately led to better labor market prospects, with early recipients of larger transfers becoming more likely to secure formal-sector employment.

Our results indicate that even temporary improvements in test scores can enhance human capital accumulation among disadvantaged students. Low-income and minority students are substantially underrepresented at selective colleges (Hoxby and Turner, 2013; Andrews et al., 2020; Mello, 2022; Barahona et al., 2023), a gap that contributes to racial wage disparities and the persistence of income inequality across generations (Chetty et al., 2020). This underrepresentation stems partly from systematic disparities in standardized test performance. Our findings suggest that interventions that boost test scores—even temporarily—can expand disadvantaged students' access to higher education and improve their long-term economic outcomes. Given the documented relationship between college selectivity and future earnings (Zimmerman, 2014; Bleemer, 2020; Machado et al., 2023),

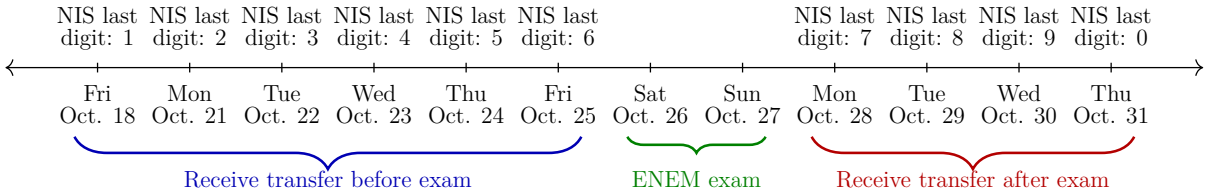
policies that improve test performance at critical junctures may serve as an important mechanism for reducing inequality in both educational attainment and labor market outcomes.

Our results suggest a previously unexplored mechanism by which persistence in low-income status can perpetuate. A precarious financial situation directly impairs performance on cognitive tasks, which subsequently influences access to education and human capital accumulation. Human capital, in turn, shapes future financial outcomes. By highlighting this linkage, our findings suggest that even temporary relaxation of liquidity constraints can meaningfully impact economic mobility when timed to coincide with high-stakes events. Information-provision policies that encourage households to shift important decisions away from low-liquidity periods could be welfare-improving if households are unaware of these cognition effects.

Finally, our findings suggest that the timing of cash transfer programs can be an effective policy tool to improve the outcomes of low-income households. There are many critical one-time events where maximizing performance or making the right decision can have long-lasting consequences (e.g., job interviews, choosing the right savings plan or insurance provider, etc.). Although personalizing transfer timing to each household's unique needs might be infeasible, offering households flexibility in selecting payment dates within a window could be a practical approach. Our results suggest that such simple modifications to existing programs could generate improvements without requiring changes to benefit levels or eligibility criteria.

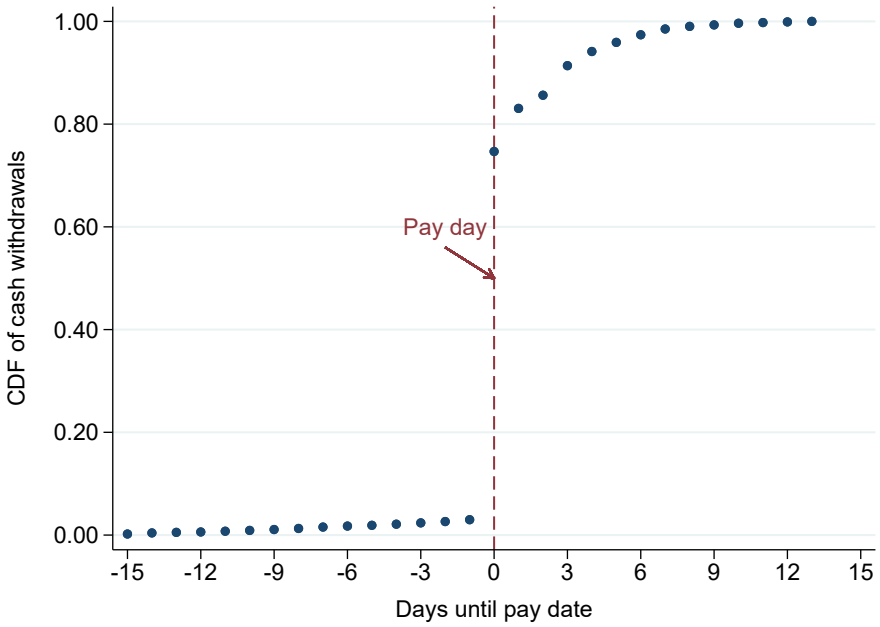
Figures and Tables

Figure 1: Timing of Bolsa Família Disbursements and ENEM Exam During October 2013



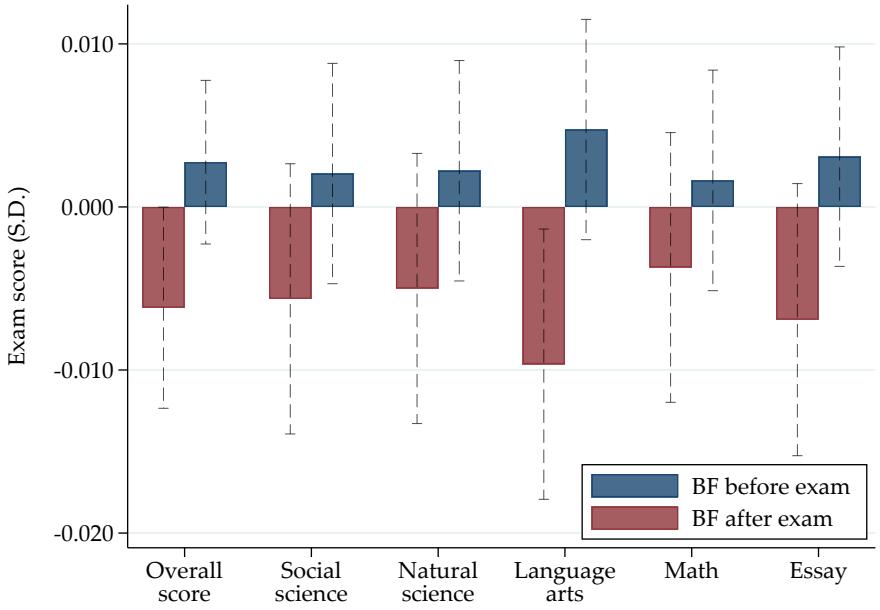
Notes: This figure shows the BFP transfer payment schedule for October 2013. Payments are sequentially disbursed across ten consecutive weekdays (excluding public holidays), typically starting on the third Monday of each month. The payment date is determined by the last digit of each beneficiary's randomly assigned NIS number. NIS numbers ending in '1' receive payment on the first day, followed by sequential payments to subsequent digits on following days.

Figure 2: Household Withdrawal Behavior Following BFP Payment Date



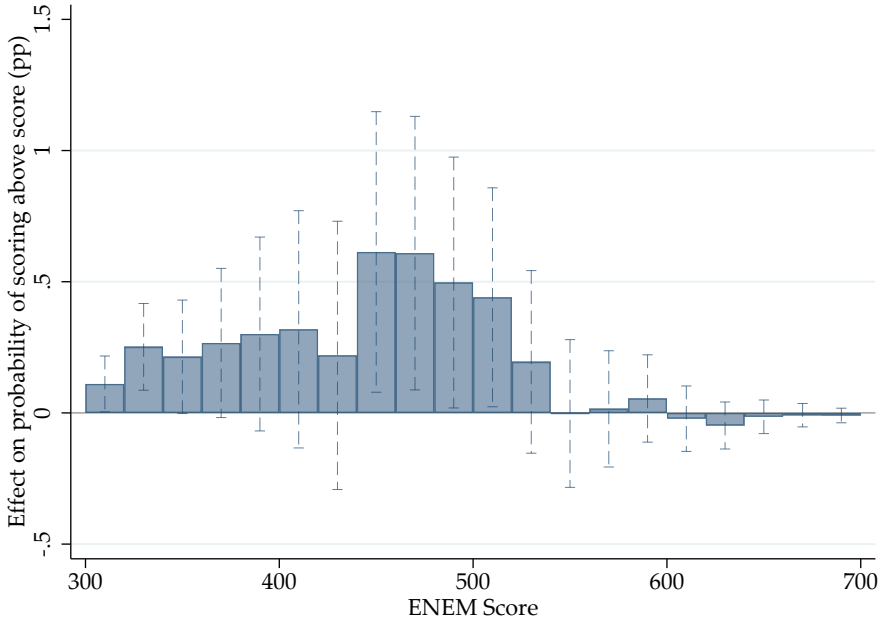
Notes: This figure shows the cumulative distribution function (CDF) of cash withdrawals relative to households' scheduled BFP payment dates. The x-axis shows days relative to the scheduled payment date (normalized to 0), while the y-axis shows the fraction of households that have withdrawn their benefits by each day. The vertical dashed line indicates the scheduled payment date. Withdrawals must be made for the full monthly benefit amount. In other words, beneficiaries make one withdrawal per month.

Figure 3: Average ENEM Scores by Subject



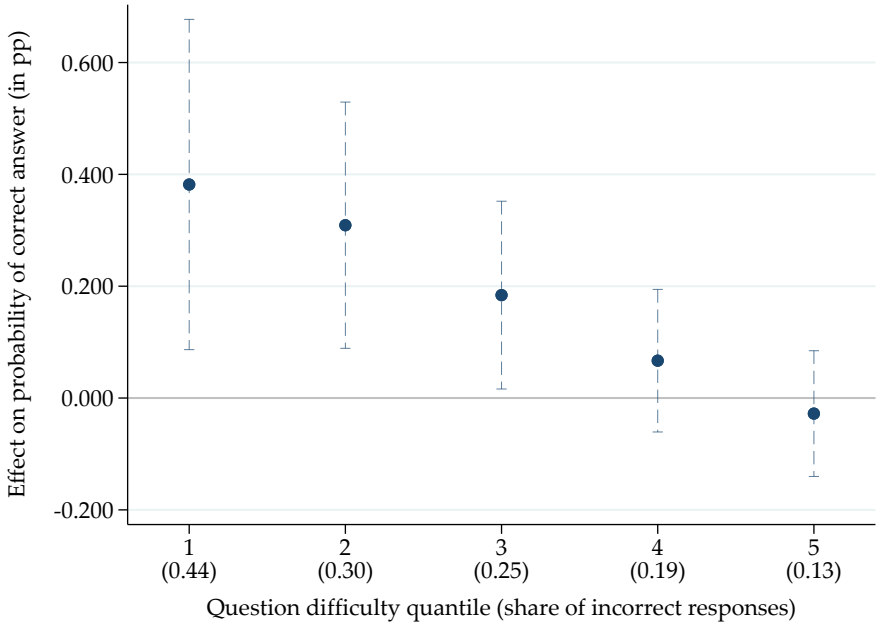
Notes: This figure shows the average standardized ENEM scores of students in households that received the BFP transfer before the exam (blue bars) to those who received it after (red bars). The overall score is computed as the average across the five subjects. Test scores are standardized to have mean zero and standard deviation one among test-takers who received BFP. Vertical dashed lines show 95 percent confidence intervals from heteroskedasticity-robust standard errors clustered at the student level.

Figure 4: Effect of BFP Payment Timing on Probability of Exceeding Score Thresholds



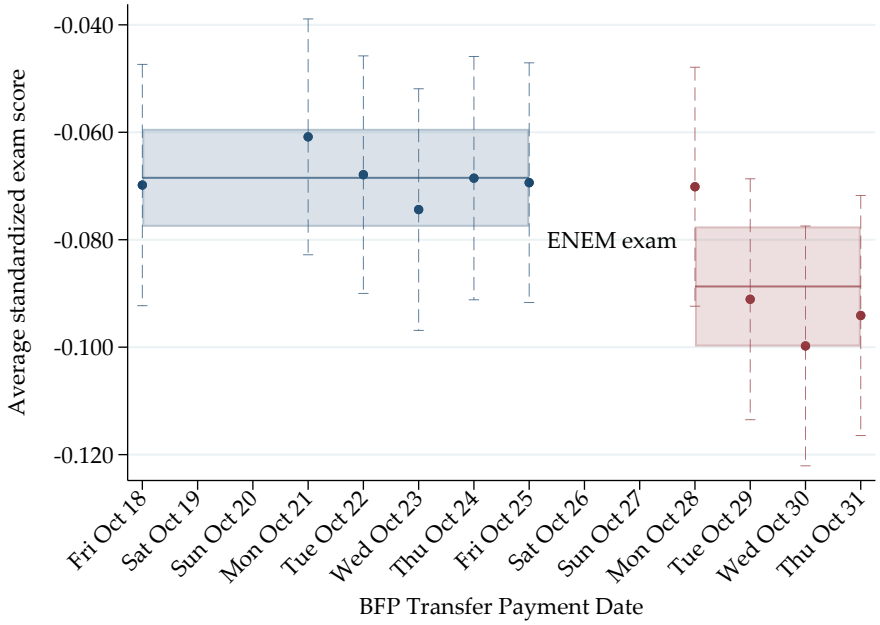
Notes: This figure shows the estimated effect (in percentage points) of receiving BFP before the ENEM exam on the probability of scoring above different score thresholds. The x-axis shows the score threshold in 20-point increments, and the y-axis shows the estimated effect, β, from equation (1). Dashed lines denote 95 percent confidence intervals from heteroskedasticity-robust standard errors clustered at the student level.

Figure 5: Effect of BFP Payment Timing on Performance by Question Difficulty



Notes: This figure shows the estimated effect (in percentage points) of receiving BFP before the ENEM exam on the probability of answering questions correctly. We classify questions into quintiles of difficulty based on the share of out-of-sample incorrect responses and estimate equation (1) at the student-question level, separately for each difficulty quintile. The y-axis shows the estimated effect for questions in the difficulty quintile denoted in the x-axis. The numbers in parentheses along the x-axis denote the share of students in the "Late" group who correctly respond to answers in each difficulty quintile. Dashed lines denote 95 percent confidence intervals from heteroskedasticity-robust standard errors clustered at the student level.

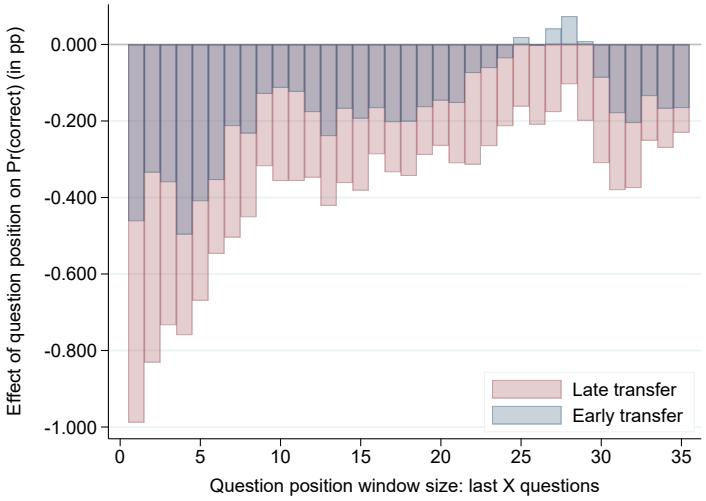
Figure 6: Average ENEM Scores by BFP Transfer Payment Date (Large-Transfer Beneficiaries)



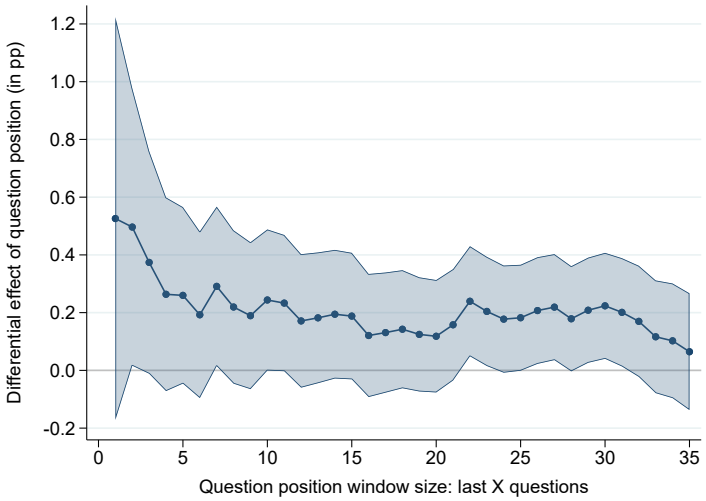
Notes: This figure shows the average standardized ENEM score and corresponding 95 percent confidence intervals (y-axis) by the 10 possible BFP cash transfer payment dates (x-axis). The sample is restricted to beneficiaries in the top tercile of transfer size. Payments are sequentially disbursed across ten consecutive weekdays (excluding public holidays), typically starting on the third Monday of each month. The payment date is determined by the last digit of each beneficiary's randomly assigned NIS number. The horizontal lines and shaded areas display the mean score and associated confidence interval for students whose household was paid before the ENEM exam (LHS) and after the exam (RHS).

Figure 7: Panel A. Fatigue-Buffering Effects of Transfer Timing

Panel A. The Effect of Question Position by Transfer Timing



Panel B. Differential Fatigue Effects by Transfer Timing



Notes: This figure shows that receiving the transfer before the exam buffers against cognitive fatigue. Panel A plots how the probability of answering a question correctly diminishes when that same question appears later in the exam. Specifically, we estimate the following regression at the student-question level:

$$\text{Correct}_{ij} = \delta_j + \beta \text{Early}_i + \phi^n \text{LastQuestions}_{ij}^n + \gamma^n (\text{Early}_i \times \text{LastQuestions}_{ij}) + \mu_{ij},$$

where Correct_{ij} indicates whether student i correctly answered question j, δ_j are question fixed effects, and $\text{LastQuestions}_{ij}^n$ indicates whether question j appears among the last n questions of either test day. We cluster standard errors at the student level. Panel A plots the coefficient on ϕ^n, the impact of question position on the probability of correctly answering a question among Late recipients, in red. The impact of question position on performance among Early recipients is plotted in blue. Panel B plots the estimates on γ^n, capturing the difference in the performance effect of question position between Late and Early recipients. The shaded blue area denotes confidence intervals at the 95% confidence level. Positive values indicate that the negative effect of question position on performance is smaller among Early recipients.

Table 1: Summary Statistics

	High school	In Cadastro Unico?		In Bolsa Familia?	
	seniors	Yes	No	Yes	No
	(1)	(2)	(3)	(4)	(5)
Panel A. Demographic characteristics and race					
Age	18.864	20.575	18.435	20.520	18.650
Female	0.588	0.632	0.577	0.652	0.580
White	0.465	0.324	0.500	0.276	0.489
Black/Brown	0.535	0.676	0.500	0.724	0.511
Panel B. Socioeconomic and household characteristics					
Went to a private HS	0.186	0.026	0.226	0.018	0.207
Family size	4.209	4.388	4.164	4.601	4.158
Mom completed high school	0.463	0.244	0.516	0.202	0.496
Mom completed college	0.162	0.033	0.193	0.020	0.179
Family earns above 2x M.W.	0.362	0.120	0.422	0.069	0.399
Family earns above 5x M.W.	0.043	0.001	0.053	0.000	0.048
Panel C. Geographic location					
Lives in the North	0.092	0.100	0.090	0.119	0.088
Lives in the Northeast	0.275	0.392	0.245	0.486	0.247
Lives in the Southeast	0.411	0.326	0.432	0.266	0.430
Lives in the South	0.139	0.097	0.149	0.061	0.149
Lives in the Midwest	0.084	0.085	0.083	0.068	0.086
Panel D. Exam attendance and test scores					
Took at least one test	0.855	0.782	0.873	0.784	0.864
Took all tests	0.832	0.753	0.852	0.757	0.842
Overall score	0.541	0.072	0.645	-0.001	0.604
Math	0.610	0.082	0.727	-0.001	0.681
Natural science	0.611	0.074	0.730	-0.001	0.682
Social science	0.539	0.073	0.642	-0.001	0.602
Language arts	0.553	0.082	0.657	-0.001	0.617
Essay	0.392	0.046	0.468	-0.001	0.437
Panel E. BFP benefits					
Disbursed through bank deposit	0.257	0.257	.	0.257	.
Total BF benefits value (US$)	94.379	94.379	.	94.379	.
Number of test-takers	1,616,321	324,404	1,291,917	184,895	1,431,426

Notes: This table shows the characteristics of high school seniors who registered for the ENEM exam (column 1), by household registration in the Registry of Social Programs (columns 2-3) and by BFP beneficiary status (columns 4-5). Panels A through D use ENEM administrative data, including students' socioeconomic questionnaire responses. Test scores are standardized to have mean zero and standard deviation one among BFP recipients (our estimating sample). Panel E uses administrative data from the Registry of Social Programs (Cadastro Unico) and BFP program records.

Table 2: Balance Test: Students Receiving BFP Before versus After the Exam

	Receives Bolsa Familia			
	Before exam (1)	After exam (2)	t-stat (3)	Std. Difference (4)
Panel A. Student characteristics				
Age	20.50	20.54	-1.28	-0.006
Female	0.652	0.651	0.43	0.002
White	0.276	0.276	0.00	0.000
Went to a private HS	0.977	0.977	0.00	0.000
Panel B. Socioeconomic and household characteristics				
Monthly income (US$)	197.44	198.57	-0.78	-0.004
Monthly p.c. income (US$)	47.73	47.90	-0.53	-0.003
Family size	4.602	4.600	0.25	0.001
0-17 year olds in household	1.714	1.716	-0.33	-0.002
0-2 year olds in household	0.092	0.092	0.00	0.000
Share of women in household	0.589	0.590	-0.91	-0.004
Mom completed high school	0.202	0.202	0.00	0.000
Mom completed college	0.020	0.020	0.00	0.000
Panel C. Geographical location				
Lives in the North	0.119	0.121	-1.33	-0.006
Lives in the Northeast	0.486	0.485	0.42	0.002
Lives in the Southeast	0.266	0.265	0.95	0.005
Lives in the South	0.061	0.062	-0.91	-0.004
Lives in the Midwest	0.068	0.068	0.00	0.000
Panel D. BFP benefits				
Disbursed through bank deposit	0.258	0.254	1.90*	0.009
BF Transfer Size (US$)	94.35	94.43	-0.19	-0.001
Panel E. Predicted score				
Predicted mean score	-0.023	-0.024	0.77	0.004
Number of test-takers	111,202	73,692	.	.

Notes: This table compares characteristics of students in households that received BFP before the exam (column 1) versus after the exam (column 2). Column 3 reports the t-statistic on β from estimating equation (1), using each characteristic as the outcome variable. Column 4 reports the standardized difference between the both groups. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Effect of BFP Payment Timing on ENEM Attendance

	Dependent variable:			
	Attended both days (1)	Attended any day (2)	Attended day 1 (3)	Attended day 2 (4)
BF before exam	-0.001	-0.002	-0.002	-0.001
	(0.002)	(0.002)	(0.002)	(0.002)
Mean after	0.758	0.785	0.782	0.761
N	184,894	184,894	184,894	184,894

Notes: This table reports estimates of β from equation (1). The sample includes all final-year high school students who registered for the ENEM. The outcomes are indicator variables for attending both exam days (column 1), attending any exam day (column 2), attending the first day (column 3), and attending the second day (column 4). Heteroskedasticity-robust standard errors clustered at the student level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Effect of BFP Payment Timing on Test Scores

	Dependent variable:					
	Average score	Social science	Natural science	Lang. arts	Math	Essay
	(1)	(2)	(3)	(4)	(5)	(6)
BF before exam	0.009**	0.008	0.007	0.014***	0.005	0.010*
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Mean after	-0.006	-0.006	-0.005	-0.010	-0.004	-0.007
N	140,041	140,041	140,041	140,041	140,041	140,041

Notes: This table reports estimates of β from equation (1). The sample includes final-year high school students who attended both exam days. The outcomes are the average standardized test score across all subjects (column 1) and the standardized test score in each subject (columns 2-6). Test scores are standardized to have mean zero and standard deviation one among BFP recipients (our estimating sample). Heteroskedasticity-robust standard errors clustered at the student level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effect of BFP Payment Timing on Test Scores by Transfer Size

	Dependent variable:					
	Average score	Social science	Natural science	Lang. arts	Math	Essay
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Top transfer size tercile (quantile 3)						
BF before exam	0.020***	0.020**	0.011	0.026**	0.020**	0.025**
	(0.007)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Mean after	-0.089	-0.088	-0.071	-0.113	-0.090	-0.082
N	40,520	40,520	40,520	40,520	40,520	40,520
Panel B. Middle transfer size tercile (quantile 2)						
BF before exam	0.000	-0.005	-0.000	0.002	-0.001	0.006
	(0.007)	(0.009)	(0.010)	(0.010)	(0.010)	(0.009)
Mean after	0.019	0.023	0.013	0.024	0.019	0.014
N	45,917	45,917	45,917	45,917	45,917	45,917
Panel C. Bottom transfer size tercile (quantile 1)						
BF before exam	0.008	0.010	0.010	0.016*	-0.001	0.002
	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Mean after	0.035	0.033	0.030	0.039	0.042	0.033
N	53,604	53,604	53,604	53,604	53,604	53,604
Panel D. P-values of equality of coefficients across quantiles						
$\beta_{Q1+Q2} = \beta_{Q3}$	0.065	0.084	0.263	0.516	0.143	0.082
$\beta_{Q1} = \beta_{Q2}$	0.465	0.411	0.291	0.389	0.462	0.922
$\beta_{Q1} = \beta_{Q3}$	0.200	0.263	0.583	0.849	0.382	0.114
$\beta_{Q2} = \beta_{Q3}$	0.052	0.056	0.158	0.342	0.099	0.142

Notes: This table reports estimates of β from equation (1) separately for three groups of students: those receiving transfers in the top size tercile (Panel A), middle size tercile (Panel B), and bottom size tercile (Panel C). The sample includes final-year high school students who attended both exam days. The outcomes are the average standardized test score across all subjects (column 1) and the standardized test score in each subject (columns 2-6). Test scores are standardized to have mean zero and standard deviation one among BFP recipients (our estimating sample). Heteroskedasticity-robust standard errors clustered at the student level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Effect of BFP Payment Timing on College Enrollment, Earning Potential, and Graduation

	Dependent variable:					
	Enroll college (1)	Private college (2)	Public college (3)	Earnings Potential (4)	3-year persist (5)	7-year grad (6)
Panel A. All BFP test-takers						
BF before exam	0.002	0.000	0.002	0.422	0.003	0.001
	(0.002)	(0.002)	(0.001)	(0.763)	(0.002)	(0.002)
Mean after	0.186	0.137	0.051	295.341	0.232	0.158
N	140,032	140,032	140,032	140,032	140,032	140,032
Panel B. Top transfer size tercile (quantile 3)						
BF before exam	0.007*	0.005	0.001	4.017***	0.008*	0.008**
	(0.004)	(0.003)	(0.002)	(1.358)	(0.004)	(0.003)
Mean after	0.157	0.109	0.050	275.840	0.196	0.130
N	40,515	40,515	40,515	40,515	40,515	40,515
Panel C. Middle transfer size tercile (quantile 2)						
BF before exam	-0.003	-0.005	0.001	-0.040	-0.003	-0.002
	(0.004)	(0.003)	(0.002)	(1.332)	(0.004)	(0.004)
Mean after	0.192	0.143	0.052	296.698	0.242	0.162
N	45,911	45,911	45,911	45,911	45,911	45,911
Panel D. Bottom transfer size tercile (quantile 1)						
BF before exam	0.003	0.001	0.002	-1.856	0.004	-0.001
	(0.004)	(0.003)	(0.002)	(1.261)	(0.004)	(0.003)
Mean after	0.202	0.152	0.052	308.891	0.252	0.175
N	53,606	53,606	53,606	53,606	53,606	53,606
Panel E. P-values of equality of coefficients across quantiles						
$\beta_{Q1+Q2} = \beta_{Q3}$	0.122	0.664	0.260	0.002	0.384	0.145
$\beta_{Q1} = \beta_{Q2}$	0.260	0.186	0.279	0.323	0.426	0.756
$\beta_{Q1} = \beta_{Q3}$	0.426	0.552	0.445	0.002	0.695	0.256
$\beta_{Q2} = \beta_{Q3}$	0.060	0.326	0.258	0.033	0.271	0.157

Notes: This table reports estimates of β from equation (1) for four groups: all BFP test-takers (Panel A), and students receiving transfers in the top (Panel B), middle (Panel C), and bottom (Panel D) size terciles. The sample includes final-year high school students who attended both exam days. The outcomes are indicators for enrollment in any college (column 1), a private college (column 2), and a public college (column 3), expected early-career earnings in USD (column 4), and indicators for persistence three years after the ENEM exam (column 5) and graduation seven years after the exam (column 6). See Appendix C.1 for variable definitions. Heteroskedasticity-robust standard errors clustered at the student level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Mechanisms for College Enrollment Effects Among Large-Transfer Recipients

	Dependent variable:				
	Selective admit	Number Scholarship Cutoffs Cleared	Share Scholarship Cutoffs Cleared	Scored $\geq$ Cutoff	Enrolled Scholarship
	(1)	(2)	(3)	(4)	(5)
BF before exam	-0.000**	12.7**	0.0058**	0.007**	0.008
	(0.002)	(5.52)	(0.37)	(0.003)	(0.010)
Mean after	0.044	284	0.103	0.193	
N	40,508	40,508	40,518	40,518	6,606

Notes: This table reports estimates of β from equation (1) for students receiving transfers in the top transfer size tercile. The sample includes final-year high school students who attended both exam days. Column headers show the outcomes: admission into university through selective (test-based) process (1), scoring above the key threshold that determines scholarship receipt in the student's state (2), scholarship receipt conditional on college attendance (3). Heteroskedasticity-robust standard errors clustered at the student level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Effect of BFP Payment Timing on Labor Market Outcomes

	Dependent variable (measured 5–9 years after ENEM)			
	Formal employment (1)	Earnings (if employed) (2)	Earnings (unconditional) (3)	Hourly wage (if employed) (4)
Panel A. All BFP test-takers				
BF before exam	-0.000	1.230	0.847	0.015
	(0.003)	(1.616)	(1.181)	(0.018)
Mean after	0.623	362.831	330.548	2.191
N	140,041	96,864	140,041	96,794
Panel B. Top transfer size tercile (quantile 3)				
BF before exam	0.010**	2.178	2.315	-0.008
	(0.005)	(2.710)	(1.942)	(0.032)
Mean after	0.594	352.667	316.613	2.140
N	40,520	27,134	40,520	27,113
Panel C. Middle transfer size tercile (quantile 2)				
BF before exam	-0.004	1.469	0.551	-0.004
	(0.005)	(2.875)	(2.107)	(0.033)
Mean after	0.626	362.596	331.286	2.208
N	45,917	31,896	45,917	31,870
Panel D. Bottom transfer size tercile (quantile 1)				
BF before exam	-0.005	0.548	0.030	0.048*
	(0.004)	(2.728)	(2.024)	(0.028)
Mean after	0.641	370.194	340.427	2.212
N	53,604	37,834	53,604	37,811

Notes: This table reports estimates of β from equation (1) for four groups: all BFP test-takers (Panel A), and students receiving transfers in the top (Panel B), middle (Panel C), and bottom (Panel D) size terciles. The sample includes final-year high school students who attended both exam days. The outcomes, measured using RAIS administrative data during 2018–2022 (5–9 years after the exam), are: formal employment (indicator for any formal employment during the period), monthly earnings among the employed (average earnings in years with formal employment), monthly earnings including imputed informal sector earnings (where non-formal workers are assigned their state's mean informal sector earnings from PNAD Contínua), and hourly wages among the employed (monthly earnings divided by contracted monthly hours). See Appendix C.1 for variable definitions. Heteroskedasticity-robust standard errors clustered at the student level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

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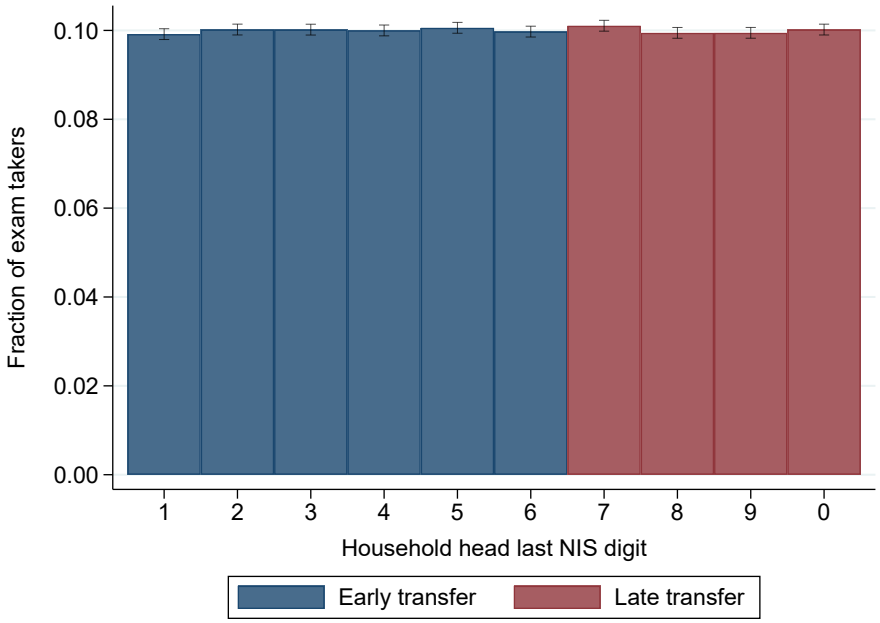
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Appendix

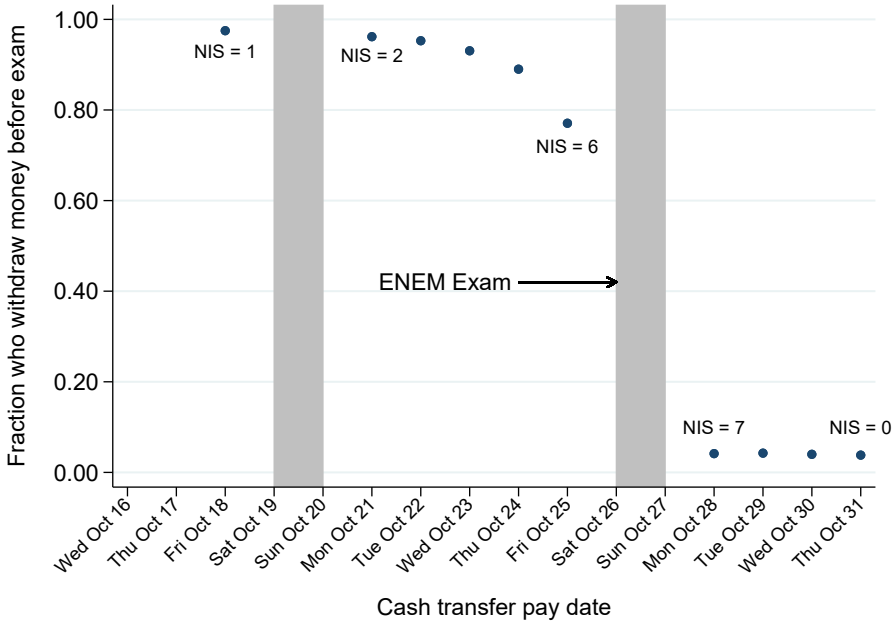
A Appendix Figures and Tables

Figure A1: Distribution of NIS Last Digits Among Students in 2013



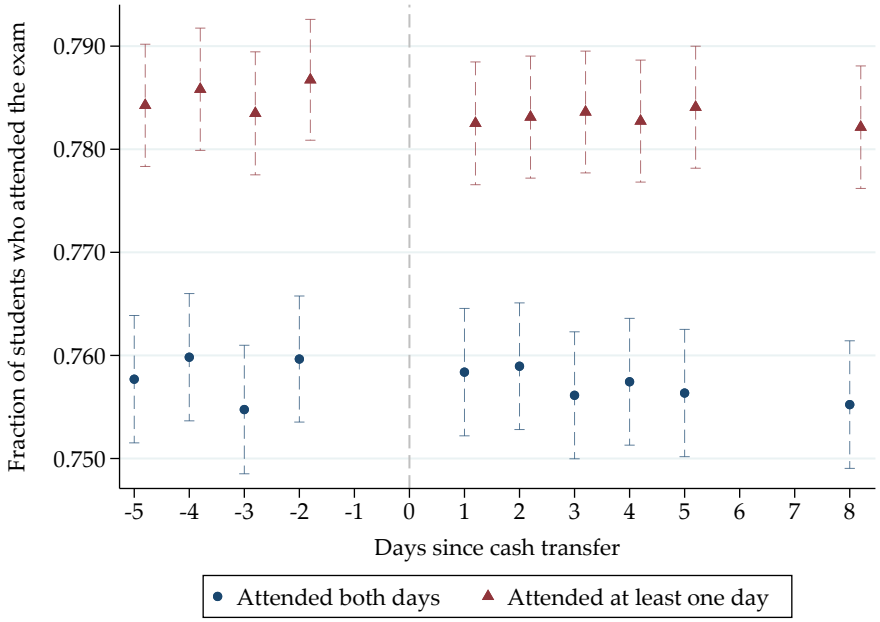
Notes: This figure shows the distribution of students by the last digit of their household's NIS in 2013. Blue bars represent households that received their BFP transfer before the ENEM exam, while red bars represent households that received it after.

Figure A2: Share of Households Withdrawing BFP Before the ENEM by NIS Last Digit



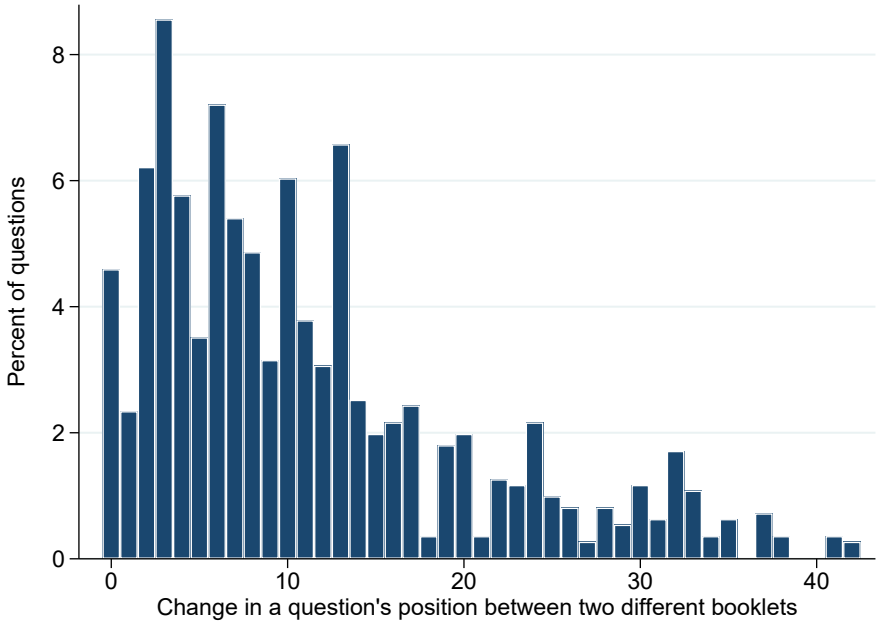
Notes: This figure shows the fraction of households that withdrew their October 2013 BFP payment by Friday, October 25 (the day before the ENEM exam), separately by NIS last digit. Payment disbursement began on Monday, October 21 for NIS ending in 1, proceeding sequentially on subsequent business days. Gray shaded areas indicate weekends.

Figure A3: ENEM Attendance Rates by BFP Payment Date Relative to Exam



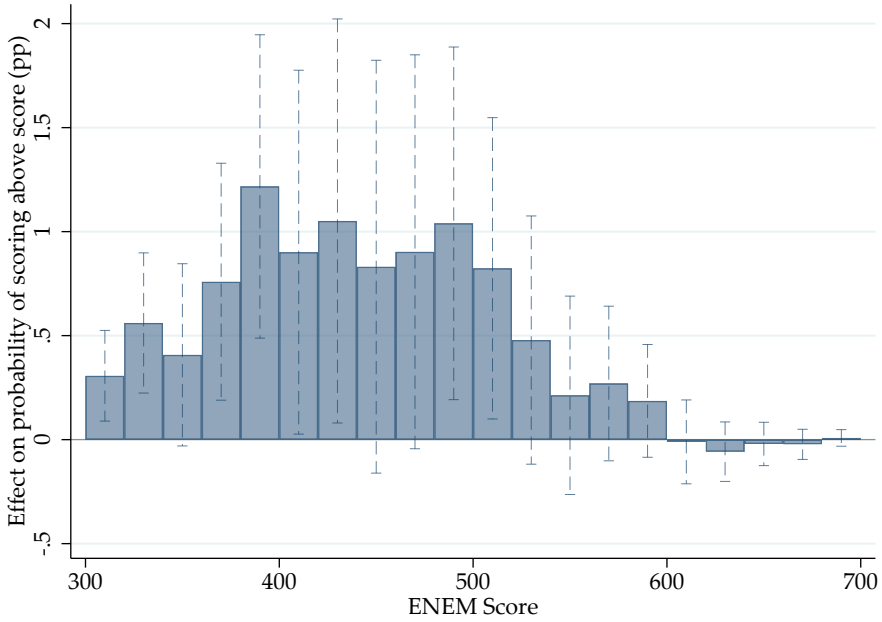
Notes: This figure shows the proportion of registered students who attended both exam days (blue circles) or at least one exam day (red triangles) by days between BFP disbursement and the exam (x-axis). Positive x-axis values indicate students whose households received BFP before the ENEM exam, while negative values indicate those who received it after.

Figure A4: Histogram of the Change in a Question's Position Across Exam Booklets



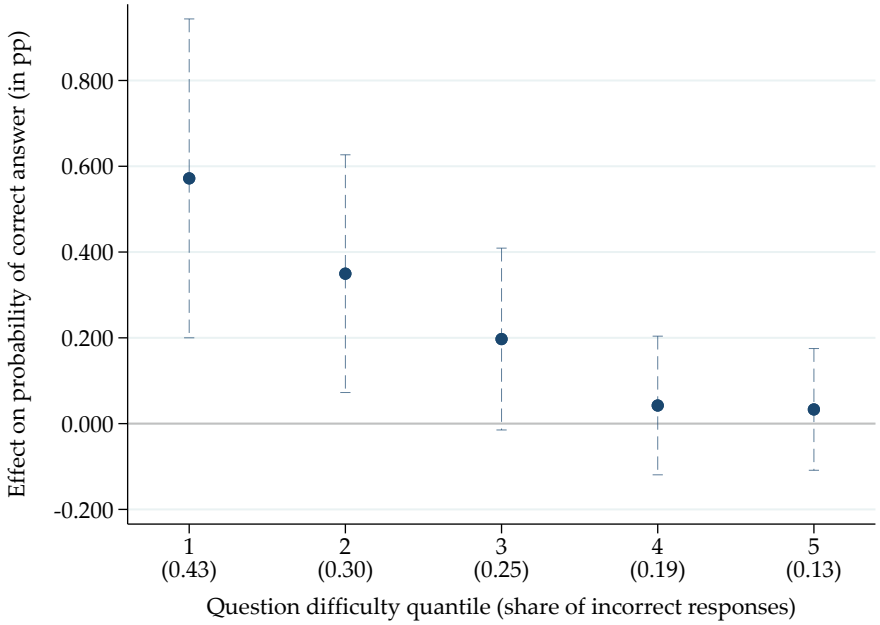
Notes: This figure shows the amount of variation available in a given question's position between different exam booklets in 2013. To construct this figure, we first calculate the difference (in absolute value) in a question's position in two exam booklets. This difference ranges from zero (if a question is in the same position in two different booklets) to 44 (if a question is in the first position of a section in one booklet and the last position of a section in another booklet). We repeat this process for each question and each possible booklet pair. The figure plots the resulting histogram of position differences.

Figure A5: Effect on Probability of Exceeding Score Thresholds Among Large-Transfer Recipients



Notes: This figure shows the estimated effect (in percentage points) of receiving BFP before the ENEM exam on the probability of scoring above different score thresholds. The sample is restricted to large-transfer recipients (top transfer size tercile). The x-axis shows the score threshold in 20-point increments, and the y-axis shows the estimated effect, β, from equation (1). Dashed lines denote 95% confidence intervals from heteroskedasticity-robust standard errors clustered at the student level.

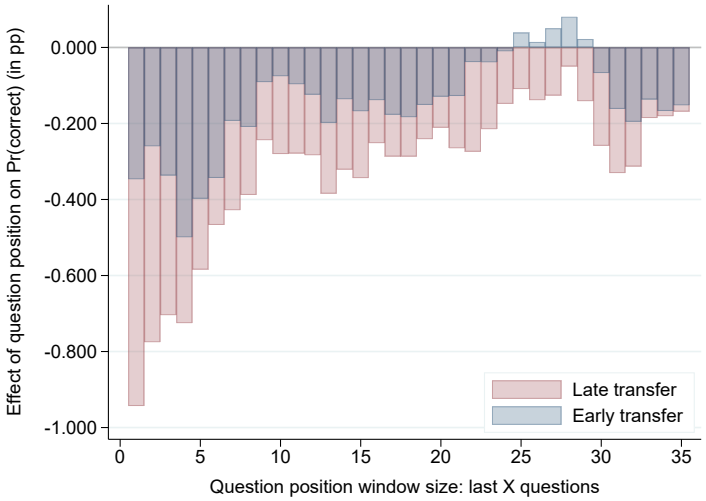
Figure A6: Effect of BFP Payment Timing on Performance by Question Difficulty, Large Transfer Recipients



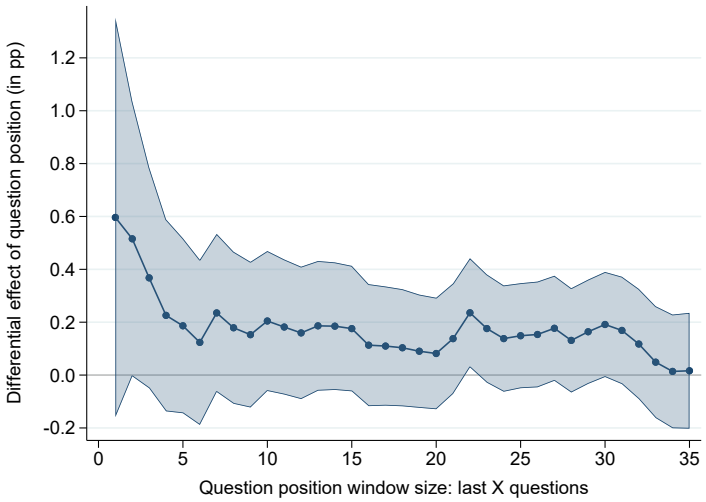
Notes: This figure shows the estimated effect (in percentage points) of receiving BFP before the ENEM exam on the probability of answering questions correctly. The sample is restricted to students in the top transfer size tercile. We classify questions into quintiles of difficulty based on the share of out-of-sample incorrect responses and estimate equation (1) at the student-question level, separately for each difficulty quintile. The y-axis shows the estimated effect for questions in the difficulty quintile denoted in the x-axis. The numbers in parentheses along the x-axis denote the share of students in the "Late" group who correctly respond to answers in each difficulty quintile. Dashed lines denote 95 percent confidence intervals from heteroskedasticity-robust standard errors clustered at the student level.

Figure A7: Panel Fatigue-Buffering Effects of Transfer Timing (Students Answering All Questions)

Panel A. The Effect of Question Position by Transfer Timing



Panel B. Differential Fatigue Effects by Transfer Timing

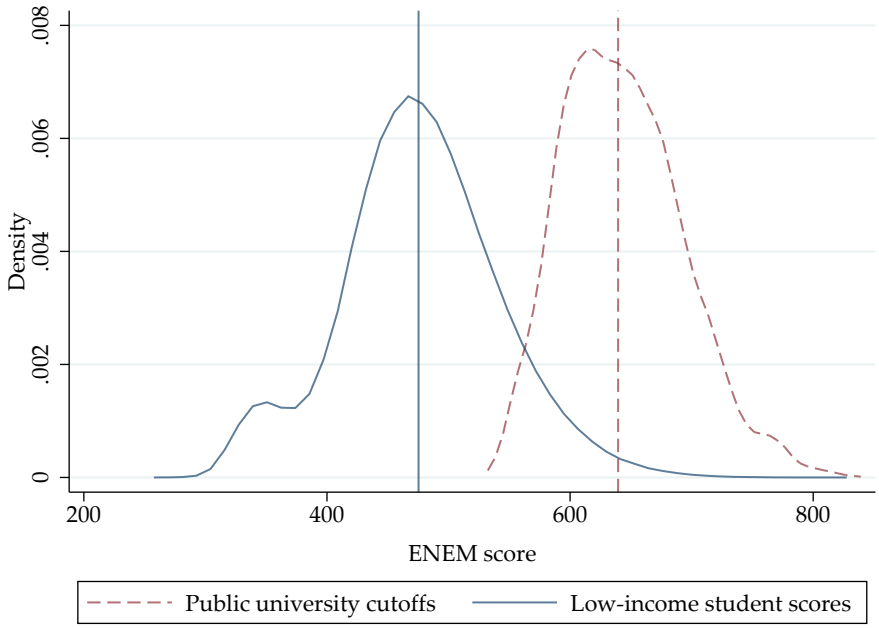


Notes: This figure shows that receiving the transfer before the exam buffers against cognitive fatigue. Panel A plots how the probability of answering a question correctly diminishes when that same question appears later in the exam. Specifically, we estimate the following regression at the student-question level:

$$\text{Correct}_{ij} = \delta_j + \beta \text{Early}_i + \phi^n \text{LastQuestions}_{ij}^n + \gamma^n (\text{Early}_i \times \text{LastQuestions}_{ij}) + \mu_{ij},$$

where Correct_{ij} indicates whether student i correctly answered question j, δ_j are question fixed effects, and $\text{LastQuestions}_{ij}^n$ indicates whether question j appears among the last n questions of either test day. We cluster standard errors at the student level. Panel A plots the coefficient on ϕ^n, the impact of question position on the probability of correctly answering a question among Late recipients, in red. The impact of question position on performance among Early recipients is plotted in blue. Panel B plots the estimates on γ^n, capturing the difference in the performance effect of question position between Late and Early recipients. The shaded blue area denotes confidence intervals at the 95% confidence level. Positive values indicate that the negative effect of question position on performance is smaller among Early recipients. The sample is restricted to students that answer all exam questions.

Figure A8: Distribution of ENEM Scores and Public University Admission Cutoffs



Notes: This figure shows the distribution of 2017 admission cutoff scores across public university programs (red dashed line) and the distribution of 2017 ENEM scores among students with family income below the minimum wage (solid blue line). Admission cutoffs come from SISU, the centralized system used by the Ministry of Education to allocate students to public universities based on ENEM scores. Vertical dashed and solid lines show median admission cutoff and ENEM scores, respectively.

Table A1: Average Student Characteristics by Last NIS Digit

	Last NIS digit:											
	1	2	3	4	5	6	7	8	9	0	F	p-val.
Panel A. Student characteristics												
Age	20.45	20.64	20.53	20.42	20.54	20.46	20.51	20.55	20.56	20.55	2.05	0.030
Female	0.651	0.657	0.648	0.650	0.653	0.653	0.651	0.649	0.650	0.654	0.61	0.794
White	0.282	0.278	0.276	0.275	0.269	0.276	0.272	0.278	0.277	0.276	1.08	0.373
Went to a private HS	0.018	0.020	0.018	0.018	0.019	0.018	0.020	0.018	0.017	0.019	0.84	0.583
Panel B. SES and household characteristics												
Monthly income (US$)	198.06	197.01	197.73	198.14	196.05	197.57	197.66	199.89	198.54	198.19	0.53	0.856
Monthly p.c. income (US$)	47.78	47.72	47.73	47.82	47.63	47.68	47.84	48.20	48.01	47.57	0.35	0.957
Family size	4.594	4.596	4.605	4.606	4.603	4.608	4.596	4.590	4.595	4.621	0.56	0.828
0-17 year olds in household	1.714	1.717	1.708	1.717	1.714	1.712	1.701	1.717	1.711	1.737	1.12	0.344
0-2 year olds in household	0.092	0.093	0.091	0.092	0.093	0.094	0.092	0.089	0.094	0.093	0.35	0.959
Share of women in household	0.589	0.592	0.587	0.593	0.589	0.588	0.592	0.587	0.588	0.592	1.80	0.062
Mom completed high school	0.196	0.202	0.206	0.205	0.202	0.200	0.200	0.201	0.203	0.204	1.01	0.433
Mom completed college	0.021	0.020	0.020	0.022	0.021	0.019	0.020	0.020	0.019	0.021	0.73	0.685
Panel C. Bolsa Fanilia Benefits												
Disbursed through bank deposit	0.257	0.259	0.255	0.257	0.260	0.260	0.260	0.251	0.251	0.255	1.25	0.256
BF Transfer Size (US$)	94.30	94.33	94.26	94.64	94.72	93.82	93.96	94.17	94.58	95.01	0.86	0.559
Panel D. Geographical location												
Lives in the North	0.123	0.116	0.121	0.117	0.117	0.118	0.117	0.119	0.122	0.124	1.39	0.186
Lives in the Northeast	0.482	0.492	0.484	0.489	0.494	0.478	0.490	0.484	0.484	0.481	1.92	0.044
Lives in the Southeast	0.265	0.263	0.268	0.268	0.260	0.274	0.261	0.268	0.265	0.267	1.67	0.091
Lives in the South	0.063	0.063	0.058	0.060	0.062	0.060	0.065	0.063	0.059	0.060	1.57	0.118
Lives in the Midwest	0.067	0.066	0.070	0.066	0.067	0.070	0.067	0.067	0.069	0.068	0.67	0.735
Panel E. Predicted Score												
Predicted mean score	-0.021	-0.024	-0.022	-0.019	-0.024	-0.020	-0.023	-0.021	-0.024	-0.022	0.66	0.742
Number of test-takers	18,488	18,522	18,621	18,615	18,568	18,387	18,696	18,247	18,328	18,423		

Notes: This table compares the average characteristics of students according to the last digit of the NIS number associated with the BFP beneficiary in a student's household. The last NIS digit fully determines the date in which a student's family receives the cash transfer. Each column reports the average characteristic of students associated with the digit denoted in the column header. For each NIS digit d, the F-statistic and associated p-value are obtained from regressing an indicator variable that takes the value of one if the BFP beneficiary in student i's household has a last NIS digit d on the characteristics shown in panels A-C.

Table A3: Effect of BFP Payment Timing on Test Scores with Student Controls

	Dependent variable:					
	Average score	Social science	Natural science	Lang. arts	Math	Essay
	(1)	(2)	(3)	(4)	(5)	(6)
BF before exam	0.007*	0.007	0.006	0.013**	0.004	0.008
	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Mean after	-0.006	-0.006	-0.005	-0.010	-0.004	-0.007
N	140,041	140,041	140,041	140,041	140,041	140,041
Controls?	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimates of β from equation (1)controlling for student characteristics (age, gender, race, income, and parental education). The sample includes final-year high school students who attended both exam days. The outcomes are the average standardized test score across all subjects (column 1) and standardized test scores in each subject (columns 2-6). Test scores are standardized to have mean zero and standard deviation one among BFP recipients (our estimating sample). See Appendix C.1 for variable definitions. Heteroskedasticity-robust standard errors clustered at the student level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Test for Differential Selection into Exam Attendance

	Dependent variable:			
	Attended both days (1)	Attended any day (2)	Attended day 1 (3)	Attended day 2 (4)
BF before exam	-0.019	-0.013	-0.016	-0.011
	(0.019)	(0.018)	(0.019)	(0.018)
Interaction terms:				
× Age	0.000	-0.000	0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
× Female	-0.006	-0.005	-0.006	-0.005
	(0.005)	(0.005)	(0.005)	(0.005)
× White	0.007	0.002	0.007	0.002
	(0.005)	(0.004)	(0.005)	(0.004)
× Private HS	0.010	0.009	0.009	0.008
	(0.011)	(0.011)	(0.011)	(0.011)
× HH size	-0.001	-0.000	-0.001	-0.001
	(0.001)	(0.001)	(0.001)	(0.001)
× Mom HS	0.010**	0.011**	0.011**	0.011**
	(0.005)	(0.005)	(0.005)	(0.005)
× Mom College	-0.018	-0.020	-0.018	-0.020
	(0.014)	(0.013)	(0.013)	(0.013)
× Lives in North	-0.005	-0.007	-0.005	-0.007
	(0.010)	(0.010)	(0.010)	(0.010)
× Lives in Northeast	0.011	0.007	0.012	0.008
	(0.008)	(0.008)	(0.008)	(0.008)
× Lives in Southeast	0.008	0.007	0.008	0.007
	(0.009)	(0.009)	(0.009)	(0.008)
× Lives in South	0.011	0.013	0.011	0.013
	(0.012)	(0.011)	(0.012)	(0.011)
× BF in bank acc	-0.001	-0.002	-0.001	-0.002
	(0.005)	(0.004)	(0.005)	(0.004)
× Total benefits	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
× Female share	0.008	0.004	0.009	0.006
	(0.011)	(0.011)	(0.011)	(0.010)
× Members 0–17	-0.002	-0.003	-0.001	-0.002
	(0.002)	(0.002)	(0.002)	(0.002)
× Members 0–2	-0.004	0.000	-0.004	0.000
	(0.007)	(0.007)	(0.007)	(0.007)
× Members 60+	0.008	0.003	0.009	0.004
	(0.007)	(0.007)	(0.007)	(0.007)
× Monthly income	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
× Per-capita income	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)
F-test p-value	0.298	0.538	0.256	0.504
Observations	184,894	184,894	184,894	184,894

Notes: This table reports regression estimates from augmenting equation (1) to include baseline covariates and their interactions with the indicator EarlyTransfer_i. For brevity, we report only the interaction terms. Standard errors clustered at the student level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Household Characteristics by Transfer Size Tercile

	Transfer size tercile		
	Tercile 1 (Bottom)	Tercile 2 (Middle)	Tercile 3 (Top)
Transfer size (USD)	51	92	175
Monthly income excluding BFP (USD)	234	179	105
Monthly income per capita (USD)	64	40	18
BFP share of income	0.26	0.45	0.72
Household size (# members)	3.49	4.12	5.48

Notes: This table reports average household characteristics by transfer size tercile. Transfer size refers to the monthly BFP benefit amount. Monthly income and income per capita are measured in USD. BFP share of income is the ratio of monthly BFP benefits to total household monthly income.

Table A5: Effect of BFP Payment Timing on Test Scores by Transfer Tercile Controlling for Student Characteristics

	Dependent variable:					
	Average score	Social science	Natural science	Lang. arts	Math	Essay
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Top transfer size tercile						
BF before exam	0.018**	0.018*	0.009	0.023**	0.017*	0.021**
	(0.007)	(0.010)	(0.010)	(0.010)	(0.009)	(0.010)
Mean after	-0.089	-0.088	-0.071	-0.113	-0.090	-0.082
N	40,520	40,520	40,520	40,520	40,520	40,520
Panel B. Middle transfer size tercile						
BF before exam	-0.002	-0.007	-0.002	0.000	-0.003	0.004
	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Mean after	0.019	0.023	0.013	0.024	0.019	0.014
N	45,917	45,917	45,917	45,917	45,917	45,917
Panel C. Bottom transfer size tercile						
BF before exam	0.008	0.011	0.011	0.017**	0.000	0.002
	(0.006)	(0.009)	(0.009)	(0.009)	(0.008)	(0.008)
Mean after	0.035	0.033	0.030	0.039	0.042	0.033
N	53,604	53,604	53,604	53,604	53,604	53,604
Controls?	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table reports estimates of β from equation (1) controlling for students' socioeconomic and demographic characteristics, separately for three groups: students receiving transfers in the top size tercile (Panel A), middle size tercile (Panel B), and bottom size tercile (Panel C). Control variables include: household size, income, share of female household members, number of members aged 0-17, members aged 0-5, test-taker's age, gender and race, binary variables for mother's and father's educational attainment. The sample includes final-year high school students who attended both exam days. The outcomes are the average standardized test score across all subjects (column 1) and standardized test scores in each subject (columns 2-6). Test scores are standardized to have mean zero and standard deviation one among BFP recipients (our estimating sample). See Appendix C.1 for variable definitions. Heteroskedasticity-robust standard errors clustered at the student level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A6: Effect of BFP Payment Timing on Test Scores by Income Tercile

	Dependent variable:					
	Average score	Social science	Natural science	Lang. arts	Math	Essay
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Top income tercile						
BF before exam	0.001	-0.001	0.006	-0.002	-0.008	0.011
	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Mean after	0.066	0.063	0.060	0.072	0.095	0.043
N	47,491	47,491	47,491	47,491	47,491	47,491
Panel B. Middle income tercile						
BF before exam	0.005	0.009	0.001	0.012	0.001	0.001
	(0.007)	(0.010)	(0.010)	(0.010)	(0.010)	(0.009)
Mean after	0.010	0.008	0.009	0.010	0.008	0.016
N	46,059	46,059	46,059	46,059	46,059	46,059
Panel C. Bottom income tercile						
BF before exam	0.021***	0.016*	0.015	0.034***	0.025***	0.018*
	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Mean after	-0.097	-0.090	-0.085	-0.112	-0.116	-0.080
N	46,491	46,491	46,491	46,491	46,491	46,491

Notes: This table reports estimates of β from equation (1) separately for three groups of students categorized based on the share of monthly household income coming from BFP transfers: those in the top tercile of BFP income share (Panel A), middle tercile (Panel B), and bottom tercile (Panel C). The sample includes final-year high school students who attended both exam days. The outcomes are the average standardized test score across all subjects (column 1) and the standardized test score in each subject (columns 2-6). Test scores are standardized to have mean zero and standard deviation one among BFP recipients (our estimating sample). Heteroskedasticity-robust standard errors clustered at the student level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A7: Effect of BFP Payment Timing on Test Scores by Share of Income from BFP

	Dependent variable:					
	Average score	Social science	Natural science	Lang. arts	Math	Essay
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A. Top income share tercile						
BF before exam	0.018***	0.017*	0.010	0.028***	0.020**	0.017*
	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
Mean after	-0.103	-0.100	-0.088	-0.122	-0.119	-0.086
N	45,669	45,669	45,669	45,669	45,669	45,669
Panel B. Middle income share tercile						
BF before exam	0.012*	0.011	0.007	0.018*	0.010	0.013
	(0.007)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
Mean after	0.004	0.006	0.003	0.003	-0.002	0.007
N	46,737	46,737	46,737	46,737	46,737	46,737
Panel C. Bottom income share tercile						
BF before exam	-0.003	-0.004	0.005	-0.002	-0.013	0.001
	(0.007)	(0.009)	(0.010)	(0.009)	(0.010)	(0.009)
Mean after	0.077	0.073	0.067	0.086	0.106	0.055
N	47,635	47,635	47,635	47,635	47,635	47,635

Notes: This table reports estimates of β from equation (1) separately for three groups of students categorized by the share of household income coming from BFP transfers: those in the top tercile of BFP income share (Panel A), middle income share (Panel B), and bottom income share (Panel C). The sample includes final-year high school students who attended both exam days. The outcomes are the average standardized test score across all subjects (column 1) and the standardized test score in each subject (columns 2-6). Test scores are standardized to have mean zero and standard deviation one among BFP recipients (our estimating sample). Heteroskedasticity-robust standard errors clustered at the student level in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A8: Causal Forest Variable Importance

Variable	Importance
Household income	0.169
Share of income from BFP	0.134
Age of household head	0.092
Number of income earnerns	0.082
Total BF transfer size	0.072
Share of female household members	0.069
Number of income sources	0.048
Number of members aged 6-12	0.039
Test-taker's age	0.034
Household size	0.031
Number of household members aged 0-17	0.025
Number of household members aged 60+	0.021
Mother has high school degree	0.017
Number of household members aged 13-17	0.016
Test-taker is female	0.009
Number of household members aged 18-24	0.008
Household head is black/brown	0.008
Test-taker works $>$ 20 hrs/week	0.006
Number of household members aged 0-5	0.004
Number of members aged 0-2	0.003

Notes: This table ranks covariates by their importance in predicting heterogeneous treatment effects according to the causal forest estimator (Wager and Athey, 2018). Ranking is based on the "variable importance" metric, which measures the proportion of splits that are made on a given covariate across all trees in the forest

Table A9: Effect of BFP Payment Timing on Essay Score Components

		Components of the essay score:				
	Overall Score (1)	Language Proficiency (2)	Theme Development (3)	Argument Construction (4)	Coherence and Cohesion (5)	Intervention Proposal (6)
Panel A. All test-takers						
BF before exam	0.010*	0.012**	0.007	0.007	0.011**	0.005
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)
Mean after	-0.007	-0.008	-0.005	-0.005	-0.007	-0.004
N	140,040	140,040	140,040	140,040	140,040	140,040
Panel B. Top transfer size tercile						
BF before exam	0.025**	0.025**	0.027***	0.019*	0.026**	0.010
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)
Mean after	-0.083	-0.081	-0.076	-0.077	-0.077	-0.042
N	40,521	40,521	40,521	40,521	40,521	40,521

Notes: This table reports estimates of β from equation (1) for four groups: all test-takers (Panel A) and students receiving transfers in the top (Panel B), middle (Panel C), and bottom (Panel D) size terciles. The outcomes include the overall essay score (column 1) and scores on five specific competencies. *Language Proficiency* assesses mastery of formal written Portuguese, including grammar, spelling, punctuation, and syntactic accuracy. *Theme Development* evaluates comprehension of the essay prompt, adherence to the assigned topic, and integration of relevant disciplinary knowledge. *Argument Construction* measures the ability to develop a clear thesis, present well-structured arguments, and use supporting evidence effectively. *Coherence and Cohesion* examines the logical sequencing of ideas, textual unity, and appropriate use of linguistic mechanisms for connection and transition. *Intervention Proposal* assesses the development of a feasible and well-structured social intervention proposal, ensuring it aligns with the discussion and respects human rights. All scores are standardized to have a mean of zero and a standard deviation of one among BFP recipients (our estimating sample). Heteroskedasticity-robust standard errors clustered at the student level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A10: Placebo Test: Effect of Last NIS Digit on Test Scores Among Social Registry Enrollees Not in BFP

	Dependent variable:					
	Average score	Social science	Natural science	Lang. arts	Math	Essay
	(1)	(2)	(3)	(4)	(5)	(6)
BF before exam	0.007	0.004	0.006	0.006	0.010	0.008
	(0.005)	(0.007)	(0.007)	(0.007)	(0.007)	(0.006)
Mean after	0.167	0.174	0.174	0.194	0.189	0.106
N	100,334	100,334	100,334	100,334	100,334	100,334

Notes: This table reports estimates of β from a placebo version of equation (1). The sample includes students with a household member enrolled in the Registry of Social Programs (Cadastro Único) who was not a BFP beneficiary. We construct a placebo treatment variable that equals one if the household member's NIS last digit would have made them eligible for BFP receipt before the exam had they been enrolled in BFP. The outcomes are the average standardized test score across all subjects (column 1) and standardized test scores in each subject (columns 2-6). Test scores are standardized to have mean zero and standard deviation one among BFP recipients (our estimating sample). See Appendix C.1 for variable definitions. Heteroskedasticity-robust standard errors clustered at the student level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A11: Impact of BFP Payment Timing Controlling for Number of Months in Program

	Dependent variable:	
	Average score (1)	Average score (2)
Panel A. All test-takers		
BF before exam	0.009**	0.009**
	(0.004)	(0.004)
Months in BFP	-0.000***	
	(0.000)	
> median months in BFP		-0.071***
		(0.004)
Mean after	-0.006	-0.006
N	140,037	140,037
Panel B. Top transfer size tercile		
BF before exam	0.020***	0.020***
	(0.007)	(0.007)
Months in BFP	-0.000**	
	(0.000)	
> median months in BFP		-0.105***
		(0.007)
Mean after	-0.089	-0.089
Observations	40,518	40,518

Notes: This table reports estimates of β from estimating equation (1) controlling for the number of months the BFP beneficiary household has been enrolled in the social programs registry. Column (1) controls for the number of months linearly, while column (2) includes a binary variable for above median number of months enrolled. Panel A shows results for the full sample of BFP test-takers, and panel B for test-takers in the top tercile of transfer size. The outcome is the average standardized test score across all subjects (column 1). Test scores are standardized to have mean zero and standard deviation one among BFP recipients (our estimating sample). See Appendix C.1 for variable definitions. Heteroskedasticity-robust standard errors clustered at the student level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A12: Effect of BFP Payment Timing on Test Scores by Student Characteristics

	Heterogeneity dimension:			
	College-educated mother (1)	Works > 30 hours/week (2)	Female student (3)	White student (4)
BF before exam	0.008*	0.008*	0.008	0.007
	(0.004)	(0.004)	(0.007)	(0.005)
Before X het.	0.057*	0.018	0.001	0.005
	(0.031)	(0.016)	(0.009)	(0.009)
N	140,041	140,041	140,041	140,041

Notes: This table reports estimates from augmented versions of equation (1) that include indicators for student characteristics and their interactions with receiving BFP before the exam. The outcome variable is the standardized ENEM score. "BFP before exam" shows the main effect of receiving transfers before the exam, while "Before × het." shows the interaction effect with indicators for: working more than 20 hours per week (column 1), having a college-educated mother (column 2), being female (column 3), being white (column 4), and taking the exam in municipality of residence (column 5). Test scores are standardized to have mean zero and standard deviation one among BFP recipients (our estimating sample). Heteroskedasticity-robust standard errors clustered at the student level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A13: Effect of BFP Payment Timing on Test Scores by Household Composition

	Heterogeneity dimension: above median...					
	Household size	Members age 0-17	Members age 0-2	Members age 0-5	Members age 18-60	Members age $\geq$ 60
	(1)	(2)	(3)	(4)	(5)	(6)
BF before exam	0.013**	0.009*	0.008*	0.009*	0.010*	0.008*
	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.004)
Before X het.	-0.011	0.000	0.010	0.001	-0.002	0.023
	(0.008)	(0.010)	(0.014)	(0.010)	(0.008)	(0.017)
N	140,041	140,041	140,041	140,041	140,041	140,041

Notes: This table reports estimates from augmented versions of equation (1) that include indicators for household composition and their interactions with receiving BFP before the exam. The outcome variable is the standardized ENEM score. "BF before exam" shows the main effect of receiving transfers before the exam, while "Before $\times$ het." shows the interaction effect with indicators for: above-median number of female household members (column 1), above-median number of household members aged 0-2 (column 2), above-median number of household members aged 0-5 (column 3), and above-median number of household members aged 18-24 (column 4). Standardized test scores are standardized to have mean zero and standard deviation one among BFP recipients (our estimating sample). Heteroskedasticity-robust standard errors clustered at the student level are shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A14: Effect of BFP Payment Timing on College Attendance by Degree Type and Field

	Enrolled in...				
	B.A. degree (1)	Teaching degree (2)	Technical degree (3)	Non-STEM degree (4)	STEM degree (5)
BF before exam	0.003	0.003	0.001	0.006*	0.001
	(0.003)	(0.002)	(0.001)	(0.004)	(0.001)
Mean after	0.099	0.046	0.015	0.140	0.018
N	40,518	40,518	40,518	40,518	40,518

Notes: This table reports estimates of *beta* from equation (1). The sample includes final-year high school students from BFP recipient households who attended both ENEM exam days and are in the top tercile of transfer size. The outcomes are indicators for enrollment in different types of college degrees: a Bachelor's degree (column 1), a teaching degree (column 2), a technical degree (column 3), a non-STEM degree (column 4), and a STEM degree (column 5). Test scores are standardized to have mean zero and standard deviation one among BFP recipients (our estimating sample). Heteroskedasticity-robust standard errors clustered at the student level are shown in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ denote significance at the 10, 5 and 1 percent levels.

B The Causal Effect of Transfer Size on Cognition

The concentration of effects among large-transfer recipients raises the possibility that cognitive benefits increase with transfer magnitude. However, transfer size is confounded by household characteristics—larger and poorer households receive larger transfers by program design. To isolate the causal effect of transfer size, we implement a "difference-in-discontinuities" design that combines eligibility-driven variation in benefit amounts with our random variation in payment timing.

B.1 Identification and Regression Model.

Our empirical strategy exploits the sharp increase in benefits at the extreme-poverty threshold. As described in Section 2, households with per-capita income below the cutoff receive an unconditional "basic benefit" of R$70 ($43), a 46 percent increase relative to the mean transfer. This rule induces a discontinuous jump in transfer size that depends only on income relative to the threshold.[23]

In a standard fuzzy Regression Discontinuity (RD), this discontinuity could serve as an instrument for transfer size, under the standard assumption that households cannot precisely manipulate reported income at the cutoff and that potential outcomes are continuous at c. As we show below, we find evidence consistent with manipulation around the threshold. We therefore adopt an alternative strategy that relaxes this assumption.

Rather than comparing students just below versus just above the cutoff, we compare the *jumps* at the cutoff c for students whose household received the transfer *before* the exam versus *after* the exam. Any discontinuity at c that is common to both groups (including manipulation of reported income) is differenced out. This "difference-in-discontinuities" design ("DiDisc") identifies whether the causal effect of the additional R$70 transfer is larger for early recipients than for late recipients.[24] We expect the impact of the additional R$70 to be larger for early recipients, as this group has access to the funds when taking the exam. In contrast, late recipients face the exam while still liquidity-constrained—the additional R$70 arrives only after the test.[25]

[23] This variation has been used by Gerard et al. (2024) to study formal labor supply responses among BFP households and by Bergstrom et al. (2025) to quantify welfare effects of BFP reforms.

[24] Our design is similar in spirit to the difference-in-discontinuities design of Grembi et al. (2016), but in our setting "groups" are defined by payment timing rather than time periods.

[25] Note that if households below the threshold can better smooth consumption across the payment cycle due to the additional resources, this would reduce differences between early- and late recipients, biasing against finding an effect. Thus, our diff-in-disc estimate provides a conservative test of whether immediate

Formally, we estimate a local linear specification:

$$Y_i = \alpha + \pi\,\mathbb{1}\{\text{Inc}_i < c\} + \delta_1\,\text{Inc}_i + \delta_2\,\text{Inc}_i \cdot \mathbb{1}\{\text{Inc}_i < c\} + \text{Early}_i \cdot \Big[\beta + \theta\,\mathbb{1}\{\text{Inc}_i < c\} + \delta_3\,\text{Inc}_i + \delta_4\,\text{Inc}_i \cdot \mathbb{1}\{\text{Inc}_i < c\}\Big] + \eta_i \quad \text{if } |\text{Inc}_i| \leq h, \quad \text{(B1)}$$

where Inc_i is per-capita household income, which is the running variable, and c is the extreme-poverty cutoff. Our regression includes only students whose family income is within h Brazilian Reals of the extreme-poverty threshold. Our benchmark results use $h = R\$40$ and we verify robustness to alternative bandwidths.

The parameter π measures the discontinuity in Y at c among late recipients ($\text{Early}_i = 0$), and θ measures the *change* in that discontinuity for early recipients—the difference-in-discontinuities at c. Rejecting the null hypothesis that $\theta = 0$ would provide evidence that money is not equally impactful for early and late recipients; for example, $\theta > 0$ implies the transfer raises scores more for households who already received the money by the time they take the exam.

B.2 Identification Assumptions and Balance Tests.

Our main identification assumption in the DiDisc design is that, near the extreme-poverty cutoff c, any discontinuities in potential outcomes and in the density of the running variable are identical for early- and late recipients. This assumption is plausible given that payment timing is effectively random, as it depends on the last digit of the NIS number.

Balance tests provide no evidence that the DiDisc assumption is violated. Appendix Table B1 reports estimates of equation (B1) using pre-determined characteristics as outcomes. For both Late and Early recipients, we find significant differences in observable characteristics just below versus just above the threshold, consistent with non-random manipulation at the extreme poverty cutoff (columns 2 and 3). However, the DiDisc estimates shown in column 4 are statistically indistinguishable from zero, indicating that these discontinuities in characteristics are similar across Early and Late recipients, as expected given the random assignment of payment timing.

liquidity affects cognitive performance.

Table B1: Difference-in-Discontinuities Balance Tests

	Control mean (1)	RD (Early) (2)	RD (Late) (3)	Diff-in-Disc. (4)	Obs. (5)
Female student	0.635	0.019**	0.029***	-0.010	91,620
		(0.009)	(0.011)	(0.014)	
White student	0.296	0.008	0.014	-0.006	89,851
		(0.008)	(0.010)	(0.013)	
Student age	20.401	0.221*	0.269*	-0.047	91,617
		(0.113)	(0.139)	(0.179)	
Student works	0.116	-0.010**	-0.005	-0.005	91,620
		(0.005)	(0.007)	(0.009)	
Went to private high school	0.975	-0.004	0.000	-0.005	91,618
		(0.003)	(0.003)	(0.004)	
Household size	4.765	-0.404***	-0.410***	0.006	91,620
		(0.031)	(0.037)	(0.049)	
Household head is literate	0.937	-0.002	-0.001	-0.001	91,547
		(0.005)	(0.006)	(0.007)	
Share of females in household	0.586	0.020***	0.020***	0.001	91,620
		(0.004)	(0.005)	(0.007)	
Household members aged 0–17	1.904	-0.390***	-0.417***	0.027	91,620
		(0.022)	(0.027)	(0.035)	
Household members aged 0–5	0.241	-0.048***	-0.047***	-0.002	91,620
		(0.009)	(0.011)	(0.015)	
Household members aged 18–60	2.480	-0.234***	-0.287***	0.053	91,620
		(0.021)	(0.025)	(0.033)	
High-school educated mother	0.212	0.010	0.021**	-0.011	85,468
		(0.008)	(0.009)	(0.012)	
Household income (R$)	402.958	-40.534***	-44.760***	4.225	91,620
		(1.879)	(2.313)	(2.975)	

Notes: This table presents balance tests of a difference-in-discontinuities analysis at the Bolsa Família extreme poverty cutoff. Beneficiaries below this cutoff are eligible for an additional unconditional benefit. We estimate equation (B1) using the baseline characteristic, shown in each row, as the outcome. Column (1) reports the outcome mean among those ineligible for the unconditional transfer. Columns (2) and (3) report the RD estimate for the Early and Late recipients, respectively. Column (4) reports estimates of the parameter of interest θ, which captures the difference in discontinuities between Early and Late recipients. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$ denote significance at the 10, 5 and 1 percent levels.

B.3 Regression Estimates.

Table B2 reports our regression estimates, while Figure B1 provides visual evidence of the discontinuities through RD plots. We first establish that crossing the extreme-poverty threshold increases the size of BFP benefits. The first row in Table B2 shows that the value of the basic benefit increases by approximately R$16 for both Early and Late recipients (columns 2 and 3). This generates a discontinuity in total transfer size in per-capita terms

of R$5, or 17% relative to a mean of R$29 (row 2). The discontinuities are identical across Early and Late recipients, as expected (column 4).

Turning to exam performance, we first rule out that crossing the extreme-poverty threshold affects the composition of test-takers, as this would confound any treatment effects on test performance. Row 3 in Table B2 shows no discontinuities in the probability of attending the ENEM for the Early and Late group, with a similarly small and statistically insignificant DiDisc estimate of 0.003. In contrast, we find a difference in discontinuities in test scores of $\theta = 0.018$ SD (row 4): crossing the cutoff increases test scores by 0.014 SD among Early recipients, while performance decreases by 0.004 SD for Late recipients. Although the magnitude is similar to the ITT estimate of early transfer receipt among large-transfer recipients (0.02 SD), the DiDisc estimate is not statistically significant at conventional levels, likely due to the lower power of the DiDisc research design.

Despite being noisily estimated, the positive DiDisc estimate provides suggestive evidence that the additional basic benefit improves exam performance when households have access to it before the exam. This result aligns with the earlier heterogeneity analysis, which showed stronger effects among larger-transfer recipients, and indicates that part of this heterogeneity reflects the causal impact of transfer size rather than purely endogenous differences across households.

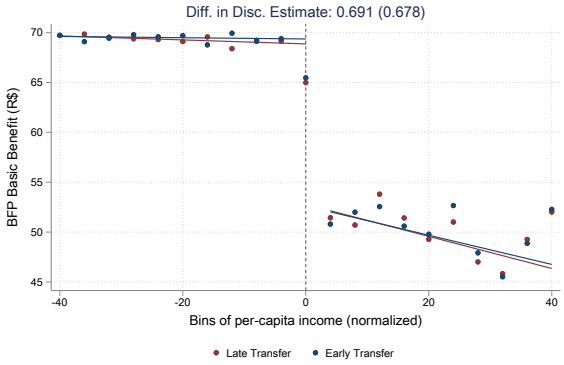
Table B2: Difference-in-Discontinuities: Transfer Size and ENEM Performance

	Control mean (1)	RD (Early) (2)	RD (Late) (3)	Diff-in-Disc. (4)	Obs. (5)
BFP Basic Benefit (R$)	49.697	16.510***	15.819***	0.691	91,620
		(0.427)	(0.530)	(0.678)	
Transfer Size per Capita (R$)	29.520	4.966***	4.998***	-0.032	91,620
		(0.228)	(0.282)	(0.361)	
ENEM attendance	0.762	0.005	0.008	-0.003	91,620
		(0.008)	(0.010)	(0.013)	
ENEM Score (SD)	0.053	0.014	-0.004	0.018	69,140
		(0.016)	(0.019)	(0.025)	

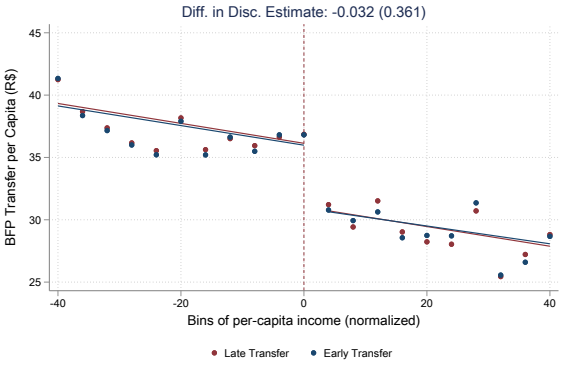
Notes: This table presents results of a difference-in-discontinuities analysis at the Bolsa Família extreme poverty cutoff. Beneficiaries below this cutoff are eligible for the "Basic Benefit," additional unconditional benefit. We estimate equation (B1) for the outcomes shown in each row: the value of basic benefits received by the household, total transfer size per capita, an indicator for attending the ENEM exam, and standardized ENEM performance. Column (1) reports the outcome mean among those ineligible for the unconditional transfer. Columns (2) and (3) report the RD estimate for Early and Late recipients, respectively. Column (4) reports estimates of the parameter of interest θ, which captures the difference in discontinuities between Early and Late recipients. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure B1: Difference in Discontinuities: Transfer size and Exam Performance

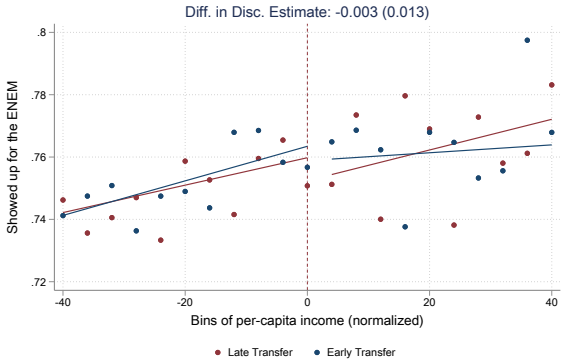
Panel A. Basic benefit Amount



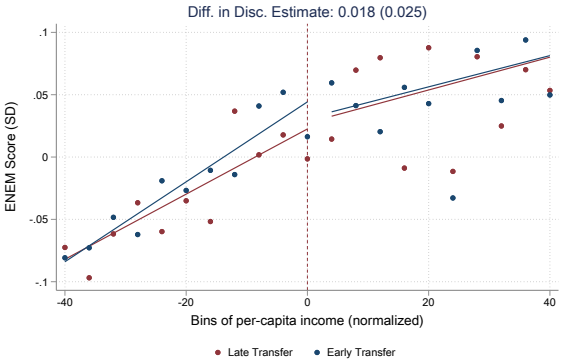
Panel B. Transfer Size Per Capita (First Stage)



Panel C. Exam Attendance



Panel D. Test Score



Notes: This figure presents a difference-in-discontinuities analysis at the Bolsa Família extreme poverty cutoff. The running variable is per capita monthly household income, and the outcome variable is shown on the y-axis. Observations below the vertical line are eligible for the unconditional basic benefit. Binned scatterplots use a bin size of 1 Real. The red and blue lines represent linear regressions fitted separately for the Early and Late transfer groups. The diff-in-disc estimate reported in the title corresponds to the interaction term (θ) in equation (B1) and captures the difference in discontinuities across groups. RD estimates for each group and the outcome mean in the ineligible group are shown at the bottom of each figure. Panel A shows the first-stage discontinuity in the basic benefit amount. Panel B shows the discontinuity in exam attendance rates. Panel C shows the discontinuity in test scores.

C Empirical Appendix

C.1 Definition of Key Variables

This appendix provides definitions of the main variables used in our analysis. We describe the construction of test score measures, educational outcomes, and labor market variables.

ENEM Outcomes

Test score. The Brazilian Testing Agency grades the ENEM exam using three-parameter item response theory (IRT). ENEM scores are scaled to have mean 500 and standard deviation 100 in the national population. We normalize test scores to have mean zero and standard deviation one in our sample.

Score threshold indicators. To examine distributional effects, we construct binary indicators for whether a student's test score exceeds various thresholds: $\mathbb{1}\{\text{TestScore}_i \geq x\}$, where x represents percentiles of the score distribution.

College Outcomes

College enrollment. We define college enrollment as an indicator for appearing in the higher education census one year after taking the ENEM.

College quality. We construct an earnings-based index of college quality by grouping all college-educated workers in the 2016–2022 employer-employee data by their university and computing the average predicted earnings at age 30 for graduates from each institution. For college graduates never observed in formal employment, we assign the average monthly earnings in the informal sector for their state of residence. Students who do not attend college are similarly assigned their state's informal sector earnings. We calculate informal earnings using Brazil's nationally-representative household survey (*Pesquisa Nacional por Amostra de Domicílios Contínua*, PNAD Contínua).

College persistence. We define indicators variables that equal one if a student is enrolled in college t years after taking the ENEM exam, for $t \in \{1, 2, 3\}$. Notice the outcome also equals one for students who do not enroll in the immediate year following the ENEM, but who enroll in subsequent years.

College graduation. We define an indicator for completing a college degree within seven years of taking the ENEM. Most students who graduate do so within this timeframe.

Financial assistance. We define an indicator that equals one for students who received any form of financial assistance when enrolling in college the year following the ENEM. This includes federal ProUni scholarships for low-income students at private colleges, as well as scholarships from state governments or universities. We measure this outcome conditional on enrollment.

Labor-Market Outcomes

Formal employment. We define formal employment as an indicator for appearing in the employer-employee data during 2018–2022. For individuals with multiple jobs, we use data from the position with the highest hours worked, using monthly earnings as a tiebreaker.

Monthly earnings. We measure average monthly earnings across all months of employment within a year. For workers appearing in multiple years during 2018–2022, we calculate the inflation-adjusted average across all observed years. We adjust for inflation using the consumer price index and express values in 2023 US dollars.

We construct two versions:

1. Earnings for test-takers *conditional* on being observed in the employee-employer dataset.

2. *Unconditional* earnings, where we impute values for test-takers never observed in formal employment using state-level informal sector earnings from PNAD Contínua.

Following the Brazilian Statistical Agency, we classify workers as informal if they lack registered employment relationships, are self-employed or employers without a CNPJ (National Registry of Legal Entities), work as unregistered domestic workers, or engage in unpaid family work.

Hourly wages. We calculate hourly wages as the ratio of inflation-adjusted monthly earnings to contracted hours per month. The data record contracted hours per week based on workers' employment contracts rather than actual hours worked. For workers observed in multiple years, we calculate the average hourly wage across all years.

C.2 Identifying Scholarship Eligibility Thresholds

This appendix describes our data-driven approach to identify score thresholds that determine scholarship eligibility across Brazilian states. Since we do not directly observe the decision-relevant aid eligibility cutoffs, we recover these thresholds from the data.

Our approach is motivated by two key features of Brazilian higher education. First, students rarely leave their home state for college (Machado and Szerman, 2021; Reyes et al., 2024), making state-level thresholds particularly relevant. Second, many scholarships are administered at the state level, creating potentially different eligibility criteria across states.

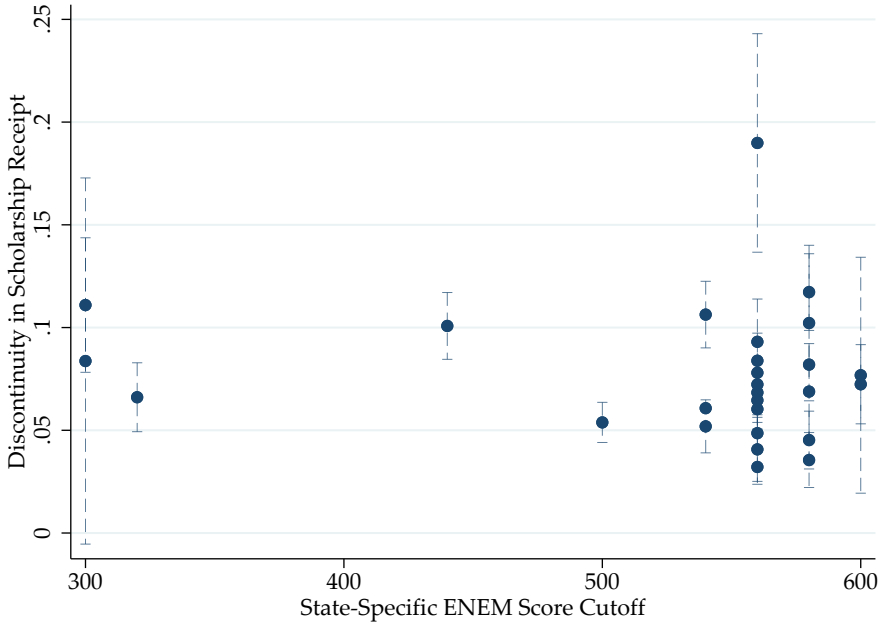
Following research on structural breaks (e.g., Card et al., 2008), we identify the score threshold in each of Brazil's 27 states where the likelihood of attending college with a scholarship increases most sharply. For each state, we estimate a series of regressions with linear trend break functions at different candidate score thresholds:

$$\begin{aligned}\text{Scholarship}_i = \beta_0 + \beta_1 \cdot \mathbb{1}(\text{ENEM}_i \geq c) + \beta_2 \cdot (\text{ENEM}_i - c) \\ + \beta_3 \cdot (\text{ENEM}_i - c) \cdot \mathbb{1}(\text{ENEM}_i \geq c) + \varepsilon_i,\end{aligned}$$

where Scholarship_i equals one if student i enrolled in college with any scholarship, and c represents a candidate threshold. We iterate over cutoffs from 300 to 700 in 20-point increments and select the cutoff that maximizes β_1, which captures the discontinuous increase in scholarship probability at the threshold.

Appendix Figure C1 displays the 27 identified thresholds and associated increases in scholarship probability. The thresholds vary across states, reflecting differences in state-level policies and competition for financial aid. The average cutoff across states occurs at 530 points, with a mean increase in scholarship-aided enrollment of 8 percentage points for students who exceed their state's threshold.

Figure C1: State-Level ENEM Score Thresholds for Scholarship Eligibility

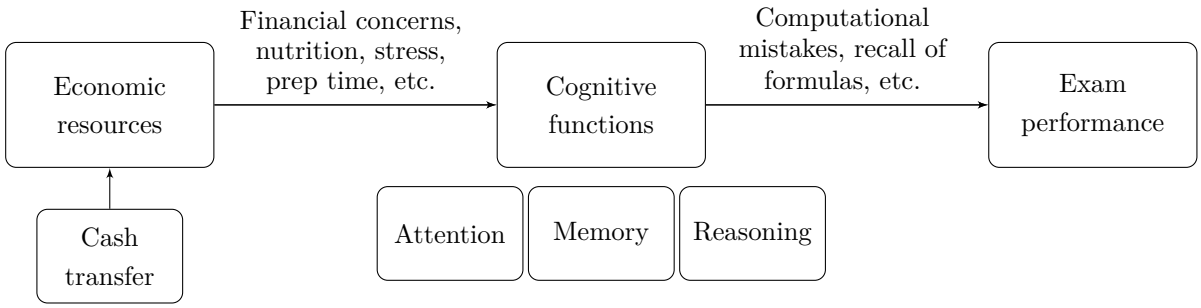


Notes: This figure displays score thresholds at which the probability of attending university with a scholarship increases most sharply in each Brazilian state. Each dot represents a state, with the score threshold on the x-axis and the discontinuous increase in scholarship probability on the y-axis. To identify these thresholds, we estimate for each state: $\text{Scholarship}_i = \beta_0 + \beta_1 \cdot \mathbb{1}(\text{ENEM}_i \geq c) + \beta_2 \cdot (\text{ENEM}_i - c) + \beta_3 \cdot (\text{ENEM}_i - c) \cdot \mathbb{1}(\text{ENEM}_i \geq c) + \varepsilon_i$, where Scholarship_i indicates enrollment with any scholarship. We iterate over cutoffs c from 300 to 700 in 20-point increments and select the cutoff maximizing β_1.

D Conceptual Framework

We present a simple framework linking monetary transfers to exam performance through cognitive functions. The framework builds on research showing that poverty can directly impair cognitive functioning (Mani et al., 2013; Schilbach et al., 2016) and that cognitive ability is a key determinant of test performance (Duckworth et al., 2011; Segal, 2012). Appendix Figure C2 illustrates these relationships.

Figure C2: Conceptual framework linking monetary transfers to exam performance



The first component links economic resources to cognitive functions. Scarcity of economic resources can negatively impact cognitive functions through both physiological and psychological channels. Limited resources may lead to poor nutrition or inadequate sleep, which directly impair cognitive ability (Bond et al., 2022; Duquennois and Jagnani, 2025). Financial scarcity may also increase stress and anxiety, consuming mental bandwidth that could otherwise be used for cognitive tasks (Duquennois, 2022; Kaur et al., 2025). The cash transfer we study provides a positive shock to household resources that could improve cognitive functioning through any of these channels.

The second component connects cognitive functions to exam performance. Successful performance on standardized tests requires sustained deployment of core cognitive functions including attention, working memory, and fluid intelligence (Ackerman, 2011). These functions affect multiple aspects of test-taking. Attention determines a student's ability to maintain focus throughout a lengthy exam and process all relevant information in complex questions (Reyes, 2023; Brown et al., 2024). Working memory enables students to hold and manipulate information while solving multi-step problems (Engle, 2002; McCabe et al., 2010; Berger et al., 2025). Fluid intelligence supports the pattern recognition and abstract reasoning needed for many exam questions (Unsworth et al., 2014).