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Education for the Poor

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Abstract

This paper investigates the impact on university enrollment of an unconditional cash transfer in Georgia, designed to help households living below the subsistence level. The program, introduced in 2005, selects recipients based upon a quantitative poverty threshold, which gives us the ability to implement a regression discontinuity design. We use data on program recipients from the Social Service Agency of Georgia (SSA) and on university admissions from the National Examination Center (NAEC) to create a single dataset and compare applicants who are above and below the threshold, while controlling for the main effect of the assignment variable itself. This paper is the first rigorous evaluation of this particular program. We find that being a program recipient significantly increases a student's likelihood of university enrollment, by 6.3%. We also find a gender specific impact on enrollment. The impact is stronger for males; being a male child of a beneficiary family results in a 13.3% greater chance of university enrollment.

Abstrakt

Práce zkoumá dopad nepodmíněného peněžního transferu, který má pomoci domácnostem žijícím pod úrovní životního minima, na přijetí dětí na vysokou školu v Gruzii. Program, který byl zaveden v roce 2005, vybírá příjemce založené na základě kvantitativního vymezení hranice chudoby, co povoluje implementovat princip regresní diskontinuity. Práce využívá údaje o příjemcích pomoci ze sociální agentury Gruzie (SSA) a data o přijatých uchazečích z Národního zkouškového centra (NAEC), což umožňuje vytvořit jednotnou databázi a porovnat uchazeče, který jsou těsně pod hranicí účasti v programu, s těmi nad hranicí, který přijímají prostředky, a zároveň povoluje zkoumat efekty programu na základě zvolené proměnné. Práce představuje první rigorózní hodnocení části programu, kde jsme odhalili, že účast v programu podstatně zvýšila pravděpodobnost přijetí na vysokou školu o 6.3%. Rovněž jsme odhalili, že dopad je silnější u mužů a u nejstaršího dítěte v rodině, kde u mužských potomků je dopad na pravděpodobnost přijetí na univerzitu o 13.3% větší. Výsledky výzkumu rovněž ukazují, že efekt je silný a rovnoměrně rozložený napříč vše lokality v zemi.

Keywords: unconditional cash transfer; university enrollment; gender;
JEL Classification: O15, I23, D13, J16

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1. Introduction

Cash transfer programs are widely used as a tool for fighting poverty. Most developing countries spend between 1% and 2% of GDP on cash transfers (DFID 2011) and international donors also invest substantially in cash transfer programs. The rationale for cash transfers is neatly summarized in Banerjee and Duflo (2011), who write that people become trapped in poverty due to geography and adversity. For those living barely above subsistence level, productivity is difficult without large investments in health and food because they must focus most of their energy on subsistence items like food and shelter simply to survive. Therefore aid is crucial in terms of dragging people out of the vicious cycle. A more skeptical view, though, is that cash transfers reduce people's incentives to solve their own problems and that cash transfer recipients may be tempted to engage in conspicuous consumption (ceremonial activities, entertainment, etc.) instead of investing in education, health and other long-term beneficial outcomes.

Ultimately, the effectiveness of cash transfer programs is an empirical question. In this project, we propose to study the impact of a cash transfer program in Georgia on enrollment in tertiary education. The program was introduced in 2005 and handed unconditional cash transfers to people living in extreme poverty. Program recipients were selected by virtue of being below a certain quantitative poverty threshold. We use this feature of the program to implement a regression discontinuity approach.

We find a positive impact of cash transfers on enrollment in tertiary education and find that being a recipient of the program significantly increases a student's likelihood of enrollment, by 6.3%. More importantly, we find that the observed effect is gender specific. The impact is stronger for males such that being a male child of a beneficiary family results in a 13.3% greater chance of being admitted to university.

Our study contributes to the growing literature on the long-run effects of cash transfers. The effects of cash transfers have emerged as an important topic in development economics. Researchers have examined the effects of cash transfers on recipients' (1) consumption patterns (Jensen & Miller, 2008;Attanasio&Messnard, 2006; Humphries, 2008), (2) savings and investments (Gertler, Martinez, &Rubio-Codina, 2006) (3) labor supply (Moffit, 1992; Bertrand, Mullainathan, & Miller; 2003; Dabalen, Kilic, & Wane, 2008).

Significant research has been devoted to the impact of cash transfers on education. De Brauw and Hoddinott (2011) study the effect of conditional (on school enrollment) cash transfers in Mexico. Using nearest neighborhood matching and fixed effects regressions, the study found that for those households who misperceived transfers as unconditional, school enrollment was significantly lower. Barrera-Osorio, Bertrand, Linden, and Perez-Calle (2008) use a randomized experiment and show cash incentives increase school attendance and graduation rates. Baird, McIntosh, and Özler (2011) performed a randomized control trial to evaluate the role of conditionality of cash transfers. They conclude that conditional cash transfers do a better job of reducing dropout rates and increasing scores in English reading tests. Oosterbeek, Ponce, and Schady (2008) evaluate the impact of cash transfer programs (aimed at increasing school attendance) on school enrollment in Ecuador and find that for the poorest households the impact is positive, while the effect disappears for the households in the second quintile in income distribution. Finally, Fack and Grenet (2015) show that provision of need based scholarships in France led to a 5% to 7% increase in university enrollment. With the exception of the latter study, previous research focused on educational achievements during primary and secondary education, while our research evaluates the impact of cash transfers on enrollment in post-secondary education. Moreover, the above studies have reported positive effects of conditional cash transfers on scholarly achievements, while in our case transfers were entirely unconditional.

Furthermore, unlike previous cash transfer programs which targeted specific groups such as micro-entrepreneurs (Blattman, Fiala, & Martinez, 2013; De Mel, McKenzie, & Woodruff, 2008), orphans (The Kenya CT-OVC Evaluation Team 2012), pensioners (Duflo, 2003) and students (Barrera-Osorio, Bertrand, Linden, & Perez-Calle, 2008; Fack&Grenet, 2015), the Georgian cash transfer program we evaluate was not directed to any particular social or age group.

Finally, studies of the impact of family income on teenage/child development and scholastic achievements generally face an income endogeneity problem. Previous literature mostly employs randomized experiments that offer very strong internal validity. However, they typically do not consider long-term outcomes, and are based on relatively small sample sizes. Observational studies thus have a useful role to play in complementing the field experimental evidence. Using regression discontinuity design in development economics program evaluation is still very rare (Duflo& Kremer, 2004; Ravallion, 2007). In order to separately identify the effects attributed to additional income from the effects of other unobserved characteristics, it is important to study the impact of exogenous variation in family income with a credible methodology such as the regression discontinuity design (Lee and Lemieux 2010).

2. The Targeted Social Assistance Program, Georgian University Admission System, and Data

2.1. The Targeted Social Assistance Program in Georgia

The dataset on Georgia's poor households was obtained from the Social Service Agency (SSA) –affiliated with the Ministry of Labor, Health and Social Assistance (MoLHSA). The agency collects national and regional data as a part of the system of means testing households which apply for the targeted social assistance program. Based on the application, a trained interviewer employed by the SSA visits a household, inspects its living standards, interviews its members, and completes a special questionnaire. Then the agency processes the information obtained and assigns a corresponding poverty score to the household (based on logarithmic sums methodology). The formula of the family score assessment combines all kinds of indices with different weights according to priority; see Formula 1 in appendix A. Families with a poverty score below a 52000 threshold were eligible for assistance until March, 2008,when the cut-off point changed to 57000 until recently. Since 2005, more than 500000 households (over 40% of Georgia's population) have applied and been assessed by the SSA. The amount of cash transferred monthly to the average household (composed of four members), is comparable to the average household's subsistence level and GDP values (per month) PPP adjusted and calculated in USD; see table A1 in appendix A. Average amounts of monthly transfer and subsistence level over 2005-2010 are 46 USD and 118 USD respectively. Thus, financial aid comprises at least 39 percent of the subsistence level income and it comes with no tax obligations attached.

Coady, Grosh, and Hoddinott (2004) examine the effectiveness of 111 cash assistance programs across 47 countries in the world. The authors define a uniform measure of effectiveness as a proportion of benefits received within each income decile. They found that Argentina had the highest effectiveness coefficient of 4, mean coefficient was 2.28 and for 109 programs the coefficient was less than 3. Using the same measure, the National Library of Georgian Parliament reports that the effectiveness coefficient of the assistance program in Georgia was 4.05, the highest in the world.

2.2. The Georgian University Admission System

In order to link the SAP to an education outcome such as university enrollments, the necessary data were acquired from the National Examination Center (NAEC), affiliated with Georgia's Ministry of Education and Science. The NAEC collects data annually on student admissions, entry examinations, and scholarship allocations relating to accredited universities in Georgia. Since the 2005 reforms, recent secondary school graduates who wish to enter university take mandatory exams (unified tests) in general skills, Georgian/foreign languages and in a fourth subject corresponding to the student's specialization. According to UNESCO data [1] (see table A2 in appendix A), Georgia, relative to other countries in transition, enjoyed high enrollment rates in the late 90s. Enrollment peaked in 2005 as the gross enrollment ratio reached about 47%. However, university enrollment fell rapidly in subsequent years and in 2010 only 28% of the university-aged population was enrolled in higher education. In the households designated as 'poor' in our data, the enrollment rates are only 12.7%, far below national rates.

2.3. Combined Dataset

Based on the identifier characteristics (Surname, Name and Birth Year) of common observations, it is possible to join the two datasets and obtain a cross-sectional sample of candidates for university applications from 2007 to 2013. As the initial poverty cut-off point (52000) increased to 57000, two datasets are considered in order to ensure that the treatment and control groups are well defined.

Dataset 1 combines information on university applicants who come from families assessed by the SSA after March, 2008. Since our main purpose is to evaluate the program's effect, we consider a treatment group with a treatment period of more than one year. In contrast, dataset 2 also includes applicants from those families who were assessed before March, 2008. Table A3 in appendix A demonstrates the quantitative distribution of applicants from SSA families. Bolded numbers refer to those candidates whose families were assessed by the SSA before the university entry examination year. The remaining numbers refer to Placebo candidates

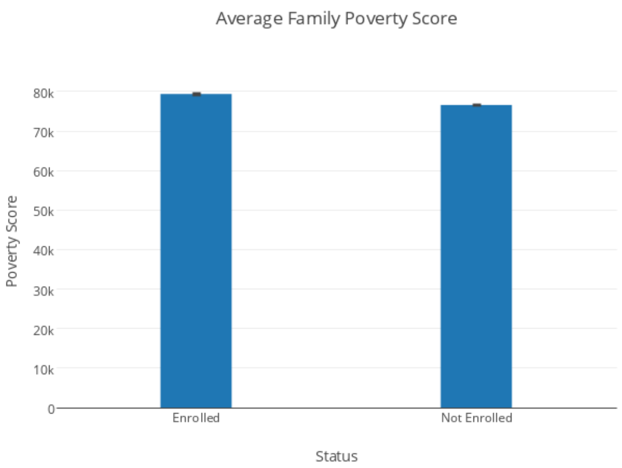
[1] The statistics we report are a gross enrollment ratio which is a share of enrolled students of the total number of people at the university age (18-23).

who took the university entry examination before the SSA assessed the families and assigned the scores.

3. Methodology and Results

Several interesting facts emerge from the initial inspection of the data. First, we see that overall, enrolled students come from wealthier families (see Figure 1)[2] and the difference is statistically significant ($P < 0.001$).

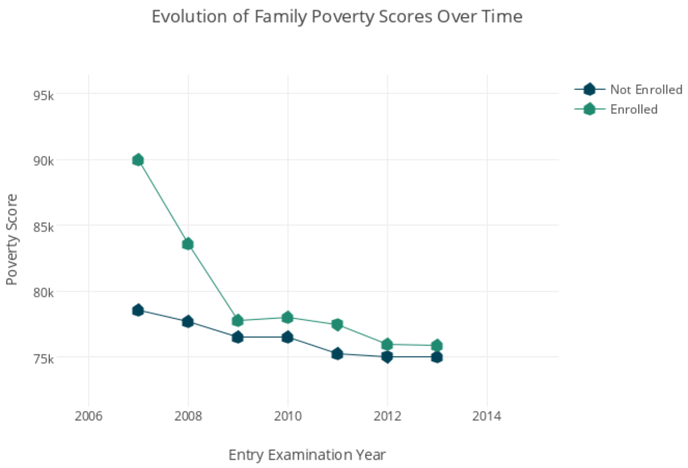
Figure 1



However, when we plot the evolution of poverty scores over time for enrolled and unenrolled students, we see a large drop in average poverty scores for enrolled students relative to unenrolled students in 2007 and a continuous decline throughout 2013 (see Figure 2), meaning that relatively more applicants from poorer families were able to enroll in universities.

[2]The higher the poverty score, the wealthier the household. Poverty scores are drawn from the random population sample.

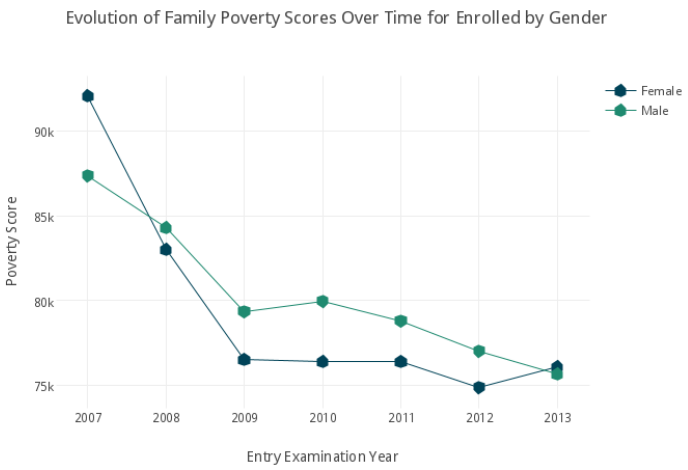
Figure 2



This is suggestive evidence that two years after its introduction, the SSA made higher education relatively more affordable for students from poor households.

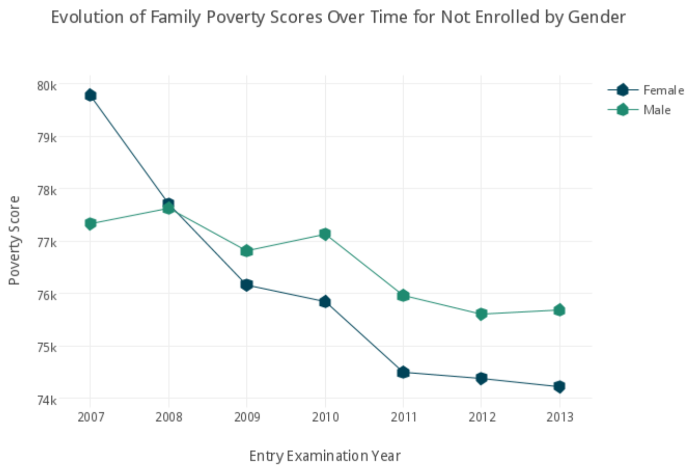
We also disaggregate poverty score time series by gender and enrollment status. Figure 3 shows that there was a large decline in average household poverty scores for enrolled females initially which leveled off later on, while the declining trend in household poverty scores for enrolled males has been steady.

Figure 3



Interestingly, according to Figure 4, the decline in average household poverty scores for unenrolled females was equally dramatic, while the decrease in household poverty scores for unenrolled males was less significant — an indication of a gender specific effect of cash transfers on university enrollment.

Figure 4



These findings call for further investigation of a causal impact of SSA on students' chances of university enrollment using a regression discontinuity methodology.

Assessment of the causal inference (average treatment effect) of the social assistance program on university enrollment can be achieved using a parametric regression discontinuity design (polynomial regression, so-called global strategy estimation) because the density of the assignment variable, university enrollment is discontinuous, while the covariates are not statistically different close to the threshold. To implement RDD analysis on the joined dataset, we first go through a visual inspection of covariates around the cut-off point. Covariates such as gender, age and number of siblings do not seem to be statistically different in the 5000 and 1000 bin widths around the thresholds, separately for Dataset 1 and Dataset 2. Covariates for dataset 1 and dataset 2, for the 5000 and 1000 poverty score intervals, are as follows:

Sample of families with a visit year after March, 2008 cut-off equals 57000 poverty score, considering dataset 1 with 5000 bin bandwidth around threshold.

	5000 poverty score around the cut-off, sample size 8709=(4893+13816)			
covariates	Treatment group	Control group	difference	t statistics
Family size	4.69	4.99	-0.31	-10.71
Number of siblings	1.61	1.62	-0.01	-0.26
Age	15.32	15.28	0.04	1.05
Gender	0.51	0.50	0.01	0.20

Sample of families with a visit year after March, 2008cut-off equals 57000 poverty score, considering dataset 1 with 1000 bin bandwidth around threshold.

	1000 poverty score around the cut-off, sample size = 3560 =(922+2638)			
Covariates	Treatment group	Control group	difference	t statistics
Family size	4.65	5.06	-0.41	-6.25
Number of siblings	1.58	1.61	-0.03	-1.09
Age	15.25	15.22	0.03	0.38
Gender	0.47	0.50	-0.03	-1.45

Sample of families with a year of visit before March,2008, cut-off equals 52000 poverty score, considering dataset 2 with 5000 bin bandwidth around threshold.

	5000 poverty score around the cut-off, sample size = 5783=(3262+ 2521)			
Covariates	Treatment group	Control group	difference	t statistics
Family size	4.64	4.49	0.15	3.60
Number of siblings	1.73	1.68	0.06	3.00
Age	13.15	13.19	-0.09	-1.57
Gender	0.53	0.53	0.53	0.01

Sample of families with a year of visit before March, 2008, cut-off equals 52000 poverty score, considering dataset 2 with 1000 bin bandwidth around threshold.

	1000 poverty score around the cut-off, sample size = 1158=(647+511)			
Covariates	Treatment group	Control group	difference	t statistics
Family size	4.43	4.48	-0.05	-0.60
Number of siblings	1.66	1.59	0.07	1.80
Age	13.17	13.08	0.09	0.70
Gender	0.53	0.56	-0.03	-0.88

In addition we have constructed outcome, ratings and covariate variables graphs for both samples, where there is a clear sign of discontinuity in case of average admissions and continuity in the case of covariates; see appendix A, Figures1–6. According to Figure 3 in appendix, we observe the discontinuity in the density of the rating variable at the threshold (57000) for dataset 1. We do not have an explanation why this might be the case. Therefore it may be argued that the allocation of cash transfers may not have been random and this may be a limitation of the study. However, our results are not driven by this particular feature of the data. This is because according to Figure 6 in appendix, the density of the rating variable is continuous at the cutoff point (52000) for dataset 2 and we still observe a positive and significant effect (also larger in size compared to the effect in case of dataset 1) of cash transfers on the enrollment. Moreover, we observe a discontinuity in the density of the family score variable around 57000 in dataset 2. That is, the discontinuity around 57000 was present before 2008 when the cutoff point was 52000, and therefore, this might be a particular characteristic of the data not related to the allocation rule of the cash transfers among the recipients.

The polynomial model, where the framework includes the entire dataset in the analysis, is as follows:

$$e_i = \alpha + \beta p_i + \gamma P^{(n)}(s_i - T) + \delta P^{(n)}(s_i - T)p_i + \theta X_i + \epsilon_i, \qquad (1)$$

where the binary outcome variable e_i stands for university enrollment, while the dummy variable p_i is one if the family is a program recipient and zero otherwise. Other explanatory parts are nth order polynomials of the distance between the poverty score and the threshold and the interactive variables, and X_i refers to the relevant covariates.

In order to specify the model or degree of the polynomial terms correctly, in this case using a parametric model, we go through a three-step procedure separately for both datasets (thresholds: 57000 and 52000). The first step is a visual inspection of the average outcome values over the rating variable and a formal test of the selection of an appropriate bin width. After choosing the optimal bin sizes, the second step is to identify the polynomials' degree. We use the methodology of Lee and Lemieux (2010) for the model selection criterion. Finally, we conduct a sensitivity analysis (robustness checks)which shows that the treatment estimates do not vary much after the outermost observations are dropped, when we are iteratively censoring the 1%, 5% and 10 % tails of the data.

By dividing intervals by equal sub-intervals up to the point when the next step brings no explanatory power to the outcome variable, the most appropriate bin size could be suggested at a poverty score of 500, because the corresponding F-statistic is not statistically significant at the 95% confidence level; see table B1 in appendix B. Table B2 in appendix B illustrates a model selection criterion. Comparing a linear model to higher order polynomial specifications, F test values suggest that a first order model with interaction terms and covariates fits best from among other options; see table B2 in appendix B. Finally, we perform a sensitivity analysis where we show that our model is not sensitive to the dropping of the outermost points from the data and the results are stable across all possible sub-samples; see table B3 in appendix B.

Based on the three-step procedure above, it was decided that the model's specification will be a parametric model with the first-degree polynomial terms with interactions and covariates. Our main findings, shown in Table 1 below, clearly suggest that being a member of a beneficiary family significantly increases chances of enrollment in university by up to 0.8 percentage point, whereas the sample mean of enrollment in our sample is 12.7%. Thus, the effect size of cash transfers on university enrollment is 6.3%. Furthermore, interaction term indicates that males have 11.8% (1.5%/0.127) higher chance compared to females.

Table 1

The Impact of the Social Assistance Program on University Enrollment: First–degree, polynomial regressions: Dataset 1

	Sample 1				Sample 2		Sample 3	
Enrollment to university	(1)	(2)	(2a)	(2b)	(3)	(4)	(5)	(6)
	Full sample	Males only	Females only	Gender gap	Oldest	Oldest males	City	City, males
Program recipient	.008**	.017***	-.005	-.003	.0073	.015*	.011	.024
	(.004)	(.006)	(.007)	(.005)	(.006)	(.008)	(.016)	(.021)
Interaction term	-	-	-	.015*	-	-	-	-
	-	-	-	(.005)	-	-	-	-
Mean	.127	.115	.141	.127	.126	.115	.125	.129
# observations	61150	31183	29967	61150	38217	19393	6924	3574
R^2	0.0021	0.0008	0.0014	0.0034	0.0017	0.0010	0.0052	0.0025

Notes: Coefficients in all columns are OLS regression estimates, robust standard errors are in parentheses; ***, **, and * indicate significance at 5%, 10% and 1% level, respectively. Samples 1, 2 and 3 are households (candidate applicants) with the entry examination at least one year later than the family assessment period. The second sample focuses on large families (more than 3 members) and the third subsample considers only households located in the capital city of Georgia. Furthermore, cohort and entry-year fixed effects and covariates (household size and gender) are considered in the regressions. Interaction term is a multiplication of male and beneficiary indicator variables.

We perform a similar analysis for dataset 2. Based on the three–step procedure (see tables B4, B5 and B6 in appendix B), it was decided that the model's specification will be a parametric model with second–degree[3] polynomial terms with interactions and covariates. According to Table 2, the effect size in this case is 11%.

[3] The model specification for dataset 2 is different from the model specification for dataset 1. This is because model specifications in each case are warranted by theory and are based on the three-step procedure Lee and

Table 2

The Impact of the Social Assistance Program on University Enrollment: Second–degree polynomial regressions: Dataset 2

	Sample 1				Sample 2		Sample 3	
Enrollment to university	(1) Full sample	(2) Males only	(2a) Females only	(2b) Gender gap	(3) Oldest	(4) Oldest males	(5) City	(6) City, males
Program recipient	.014*	.023*	.016	.008	.021**	.022*	-.017	-.012
	(.007)	(.011)	(.013)	(.012)	(.009)	(.012)	(.021)	(.029)
Interaction term	-	-	-	.004	-	-	-	-
	-	-	-	(.006)	-	-	-	-
Mean	.117	.127	.128	.117	.115	.106	.141	.136
# observations	71132	34378	36754	71132	50129	25960	11286	5802
R^2	0.0025	0.0027	0.0036	0.004	0.0027	0.0057	0.0049	0.0077

Notes: Coefficients in all columns are OLS regression estimates, robust standard errors are in parentheses; **, and * indicate significance at 5%, and 10% level, respectively. Sample definitions are the same as in the previous table. Samples 1, 2 and 3 are households (candidate applicants) with the entry examination at least one year later than the family assessment period. The second sample focuses on large families (more than 3 members) and the third subsample considers only households located in the capital city of Georgia. Furthermore, cohort and entry-year fixed effects and covariates (household size and gender) are considered in the regressions. Interaction term is a multiplication of male and beneficiary indicator variables.

Thus far we have shown that there is a statistically significant effect of UCT in Georgia on university enrollment.

In order to strengthen the validity of the regression outcomes, we present Placebo results which are the effects at the cut-off in the year before the social assistance program started. For both data sets there is no effect of the program on the university enrollment, specifically we get negative coefficient estimates (-0.01% and -2.1%) and they are not statistically significant effects. Therefore, the result we get under our identification is robust.

In light of the just-published study (Fack & Grenet, 2015) that reports up to 7% increase in university enrollment as a result of 1500 euros need-based scholarships allocated to potential students in France, the effects of the Georgian cash assistance program are particularly notable. First of all, unlike in France, cash transfers in Georgia were unconditional. Second, the amount of cash transfers to Georgian households, which never exceeded 100 US dollars for the average beneficiary family, was minuscule relative to need-based scholarships granted to students in France.

Lemieux (2010). Moreover, the datasets 1 and 2 are not identical as they are distant in time and have different cutoff points for poverty score and these may, in addition, be factors that lead to different model specifications for each datasets.

4. Heterogeneity Analysis

In this section, we extend our analysis and explore whether and how a family's composition moderates the observed effect. First of all, we are interested in whether the observed effect is gender specific. According to Thomas (1990), mothers devote windfall resources to improve the nutritional status of their daughters, while fathers disproportionally favor sons. Duflo (2003) finds that pensions received by women had large positive impact on height and weight of their granddaughters but small effect on grandsons. In light of these results, our findings are very interesting as we show that cash transfers significantly increase odds of university enrollment for males. According to Table 1 above, when we consider gender, the effect for males becomes 13.3% (18.1% in dataset 2, Table 2). This may echo reported gender specific preferences (biased towards males) of parents in South Caucasian countries (King, Guo, McKee, Richardson, and Stuckler, 2013). While cash transfers increase overall university enrollment rates in Georgia, they may also be responsible for widening the gender gap in education.

Further, there is strong evidence in other areas of economic research showing how birth order affects child outcomes. Fehr, Bernhard and Rockenbach (2008) show that the youngest children are less egalitarian. Dohmen, Falk, Huffman and Sunde (2011) investigate the intergenerational transmission of risk and trust attitudes as a result of parental socialization efforts. They find that first–born children are usually more similar to their parents in terms of risk and trust preferences. To explain this finding, the authors maintain that socialization is a result of parental effort, which seems to be stronger for oldest children. In line with these findings, we observe that the impact of cash transfers on university enrollment is stronger for the oldest children in a family; see column 3 in the Tables above. This finding is also a direct implication of the quantity-quality tradeoff paradigm formulated by Becker (Becker & Lewis, 1973) and empirically documented by Horton (1986).Column 4 in the Table above shows that this effect is stronger when the oldest child is male –consistent with the observation discussed earlier.

Finally, we check whether the effect differs across the geographical locations of the program's recipients. One might argue that the program is more likely to increase the chance of enrollment for those students who live in the capital city of Georgia (Tbilisi) and has less impact on university enrollees in the regions. Surprisingly, the Tbilisi coefficient has a negative sign, although it is not statistically significant. Still, this may suggest that the university education is costlier for students from the more rural regions. Indeed, the reported evidence shows this to be the case (Chanqseliani, 2013) and we will elaborate on this below.

5. Discussion

This paper investigates the impact of unconditional cash transfers in Georgia on university enrollment. The program selects recipients based upon a quantitative poverty threshold, which gives us the ability to implement a regression discontinuity approach. We use the data on program recipients from the SSA and on university admissions from the NAEC and combine these into a single dataset. First of all, we observe that the enrollment rate in the sample of poorest Georgian households is very low relative to national average. We find that being a recipient in the program significantly increases a student's likelihood of university enrollment, by 6.3%. For a comparison, Fack and Grenet (2015) report up to 7% increase in university enrollment as a result of a 1500 euro need-based scholarships allocated to potential university students in France. The large effects of cash transfers on enrollment rates in Georgia are particularly notable. First of all, unlike in France, cash transfers in Georgia were unconditional. Second, the amount of cash transfers to Georgian households, which never exceeded 100 US dollars for an average family, was minuscule relative to the 1500 euro scholarships in France. If unconditional transfers have such a strong impact on university enrollment by poor students, Georgian government may want to consider further complementary approaches to nudge the poor to invest in skills and education, as the university enrollment rates of poor students are still depressingly low. In particular, politicians might also opt for *conditional* transfer programs, such as need-based university scholarships that would encourage students from poor family backgrounds to continue their education. Such measures would reduce the pressure to leave the educational system and start working early with low education levels and correspondingly low productivity and income levels.

We also find a gender specific effect. While cash transfers increase overall university enrollment rates in Georgia, the effect for males is much stronger. Our findings echo previously reported gender specific effects of cash transfers (Thomas, 1990; Duflo, 2003). We also observe that the impact of cash transfers on university enrollment is stronger for the oldest children in a family. This finding is in line with the quantity-quality tradeoff paradigm which was formulated by Becker (Becker & Lewis, 1973).

Finally, as noted, the negative coefficient on Tbilisi may be an indication that cash transfers most effectively help students from rural regions, as the costs of higher education are greater for these applicants. One factor distorting educational choices is distance (James, Baldwin, & McInnis, 1999; Griffith & Rothstein, 2009). The applicants most likely to be deterred by the distance factor from applying to high ranking universities are low income (Turley, 2009) and those who are from rural areas (OECD & World Bank, 2009; Chanqseliani, 2012). The distance factor in the Georgian context is reinforced by the fact that universities do not offer student accommodation or support for living expenses, and financing student life per academic year in Tbilisi would cost an average rural adult three years of income (Chanqseliani, 2012). As a result, according to Chanqseliani (2012), rural applicants are 12 times less likely to apply to prestigious universities, most of which are located in Tbilisi[4]. Therefore, allocation of regional talent is biased towards least prestigious and peripheral universities.

Previous literature is rich with examples of when the sorting of students and universities according to prestige considerations has a very significant effect on educational outcomes, occupations, earnings and, consequently, social mobility (Behrman, Rosenzweig, &Taubman, 1996; Daniel, Black, & Smith, 1997; Brewer, Eide, & Ehrenberg, 1999; Carnevale& Rose, 2003; Li, Meng, Shi, & Wu, 2012). The misallocation of regional talent will in turn adversely impact the quality of education, that may lessen the productivity of workers and ultimately generate some degree of welfare losses in Georgia, where, despite the success of the educational reforms, the quality of education is still a significantchallenge[5] and the resulting problem of skills mismatch in labor sector is paramount[6].

As a next step, we plan to evaluate the impact of cash transfers on the educational choices of rural applicants and determine whether being a recipient of government assistance increases rural students' enrollment in high-quality Tbilisi-based universities, helping them to overcome the obstacle of distance. We are negotiating with NAEC for access to regional level student data and plan to continue our analysis as soon we receive the data.

[4]According to Chanqseliani (2012), the ranking of the universities is based on the average United National Examination scores of the student cohort. According to this measure of university quality, 100% of the highest, 100% of the second highest and 100% of the medium quality universities are located in Tbilisi. 65% of the lowest quality universities are located outside of Tbilisi.
[5]World Bank, 2012.
[6]World Economic Forum's Executive Opinion Survey, 2012.

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Appendix A

Formula 1: The Family Score Assessment methodology is based on the logarithmic sums principle that considers different weights according to the priority. $K_{i,j}$ refers to the weights and $Y_{i,j}$ to survey responses.

Welfare index	$\mathrm{I} = \frac{\mathrm{C}}{\mathrm{N}}$
Household consumption index	$C = \exp(K_0 + \sum_{i=1}^{10} C_i) - pC_0$
Agricultural index (land)	$C_1 = \sum_{i=1}^{11} K_{1,i} \ln(1+Y_{1,i})$
Agricultural index (livestock)	$C_2 = \sum_{i=1}^{4} K_{2,i} \ln(1+Y_{2,i})$
Non-agricultural index	$C_3 = \sum_{i=1}^{8} K_{3,i} \ln(1+Y_{3,i}) + \sum_{i=9}^{12} K_{3,i} Y_{3,i}$
Income index	$C_4 = K_{4,1} \ln(1+Y_{4,1})$
Demographic index	$C_5 = K_{5,1} \ln(1+Y_{5,1})$
Education and skills index	$C_7 = \sum_{i=1}^{2} K_{7,i} Y_{7,i}$
Territorial index	$C_8 = \sum_{i=1}^{10} K_{8,i} Y_{8,i}$
Interviewer index	$C_9 = \sum_{i=1}^{10} K_{9,1,i} Y_{9,1,i} + \sum_{i=1}^{4} K_{9,2,i} Y_{9,2,i} + \sum_{i=1}^{4} K_{9,3,i} Y_{9,3,i} + \sum_{i=1}^{4} K_{9,4,i} Y_{9,4,i}$
Other possessions index	$C_{10} = \sum_{i=1}^{2} K_{10,i} Y_{10,i}$
Family adult members index	$E = \sum_{i=1}^{n} e_i$
Household necessity index	$N = \frac{E}{n^{\beta}} \cdot B$
Poverty score	$Q = \max(10 \cdot \mathrm{int}(10000 \cdot I), 1000)$

Table A1: Amount of cash transferred monthly to the average household in PPP adjusted USD. All other values are calculated per month.

Year	Fixed payment	Marginal payment	4-member family cash transfer	4-member family GDP	Average family's subsistence level
2005	16.5	6.6	36.4	501.8	88.7
2006	16.9	6.8	37.1	774.6	100.6
2007	18	7.2	39.5	960.6	119.1
2008	20.1	8.1	44.3	973.7	144
2009	18	14.4	61.1	818.4	129.3
2010	16.8	13.5	57.2	874.3	126.4
2011	17.8	14.2	60.5	1076.9	156.9
2012	18.2	14.5	61.8	1174.5	153.5

Table A2: Gross enrollment rates for countries in transition.

GROSS ENROLLMENT RATIO, TERTIARY, BOTH SEXES (%): 1999-2010								
		1999-2005			2005-2010			1999-2010
	Country	% enrollment In 1999	% enrollment In 2005	**% change**	Country	% enrollment In 2010	**% change**	**% change**
Low enrollment level in 1999(below30%)	Romania	21.63	44.90	107.59	Romania	56.77	26.44	162.48
	Kazakhstan	24.93	52.92	112.24	Kazakhstan	39.49	-25.37	58.38
	Czech Rep.	25.56	48.90	91.32	Czech Rep.	63.21	29.24	147.27
	Macedonia	21.77	29.63	36.07	Macedonia	37.07	25.12	70.26
	Mongolia	26.91	44.65	65.93	Mongolia	53.81	20.49	99.95
	Slovakia	25.94	40.39	55.66	Slovakia	55.99	38.61	115.78
	Kyrgyzstan	29.16	42.53	45.82	Kyrgyzstan	42.13	-0.94	44.44
	Tajikistan	17.44	20.96	20.14	Tajikistan	22.69	8.27	30.08
	Armenia	34.62	38.36	10.82	Armenia	50.62	31.94	46.22
	Uzbekistan	12.50	9.85	-20.88	Uzbekistan	9.94*	0.91	-20.48
	Azerbaijan	15.72	14.45	-8.07	Azerbaijan	19.26	33	22
High enrollment level in 1999(above30%)	Hungary	32.49	65.10	100.33	Hungary	60.37	-7.26	85.78
	Lithuania	44.01	77.50	76.10	Lithuania	80.75	4.18	83.47
	Slovenia	52.35	79.70	34.31	Slovenia	88.46	10.99	68.97
	Latvia	50.90	78.85	54.90	Latvia	70.55	-10.53	38.59
	Croatia	30.55	44.53	45.74	Croatia	55.83	25.37	82.73
	Ukraine	47.10	68.66	45.78	Ukraine	76.65	11.63	62.74
	Poland	45.43	63.60	39.97	Poland	73.52	15.59	61.80
	Russia	51.44	72.59	41.09	Russia	75.89	4.54	47.53
	Estonia	51.12	68.44	33.89	Estonia	71.65	4.68	40.16
	Georgia	35.70	46.60	30.51	Georgia	28.26	-39.34	-20.84
	Belarus	52.11	66.16	26.96	Belarus	78.99	19.38	51.56
	Moldova	32.69	36.09	10.40	Moldova	38.14	5.67	16.67
	Bulgaria	45.20	44.27	-2.05	Bulgaria	57.99	30.99	28.29

Table A3: Quantitative distribution of candidate applicants (ready for higher education) from SSA families, where numbers in bold refer to those candidates whose families were assessed before the entry examination year

		University entry Examination Year							
Threshold	Family assessment year (by SSA)	2007	2008	2009	2010	2011	2012	2013	Total
T=52k	2005	**842**	**943**	**746**	**658**	**584**	**527**	**531**	4831
	2006	**5582**	**6051**	**5,599**	**4904**	**4564**	**4579**	**4476**	35755
	2007	4036	**4418**	**4425**	**4105**	**3865**	**3924**	**3875**	28648
T=57k	2008	6803	6460	**5863**	**5735**	**5727**	**6024**	**5771**	42383
	2009	10497	11081	9668	**8778**	**9259**	**9346**	**9530**	68159
	2010	718	753	703	644	**602**	**608**	**565**	4593
	Total	28478	29706	27004	24824	24601	25008	24748	184369
	Enrollment								
	no	25165	26913	23687	22109	21564	21708	21318	162464
	yes	3313	2793	3317	2715	3037	3300	3430	21905
	% enrollment	12%	9%	12%	11%	12%	13%	14%	12%
	NAEC	15599	14159	25153	19749	23204	24495	27097	149456
	% share in NAEC	21%	20%	13%	14%	13%	13%	13%	15%

Figure 1: (Data set 1) – Distribution of the covariates (Family size, age, number of siblings, gender).

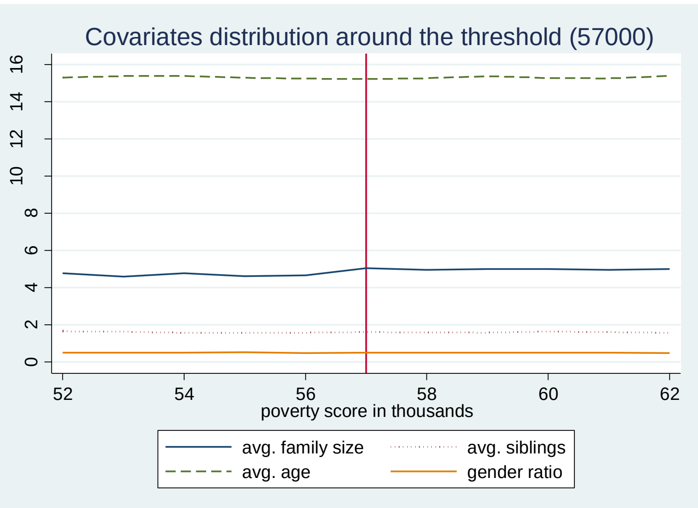


Figure 2: (Data set 1) – Average enrollment rate across bins. The solid lines refer to a 5 000 poverty score neighborhood around cut-off.

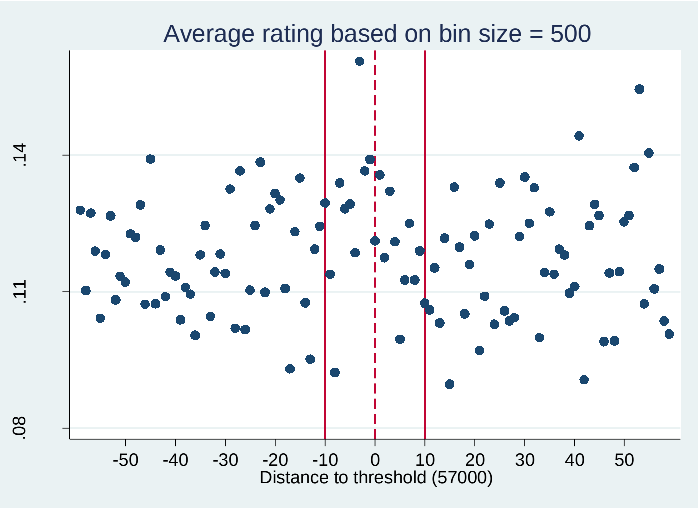


Figure 3: (Data set 1) – Density of rating variable. There is a sign of discontinuity.

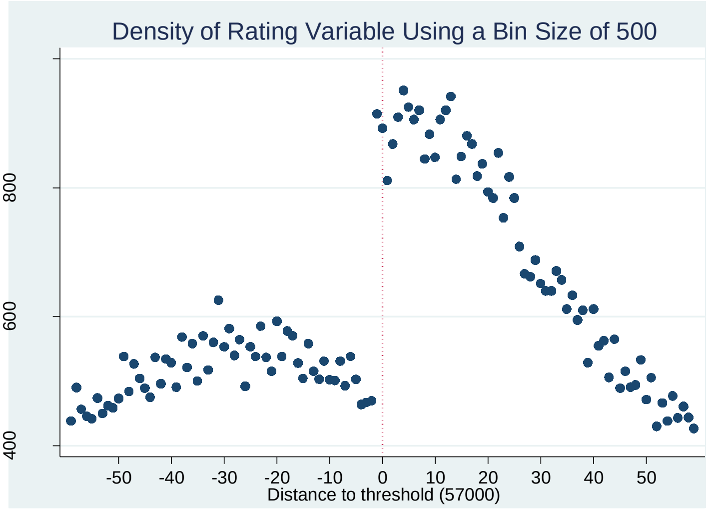


Figure 4:(Data set 2) – Distribution of the covariates (Family size, age, number of siblings, gender).

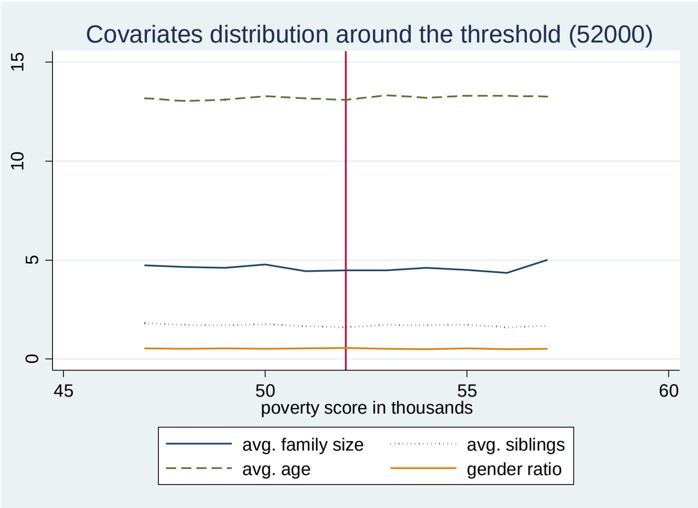


Figure 5:(Data set 2) – Average enrollment rate across bins. The solid lines refer to a 5000 poverty score neighborhood around cut-off.

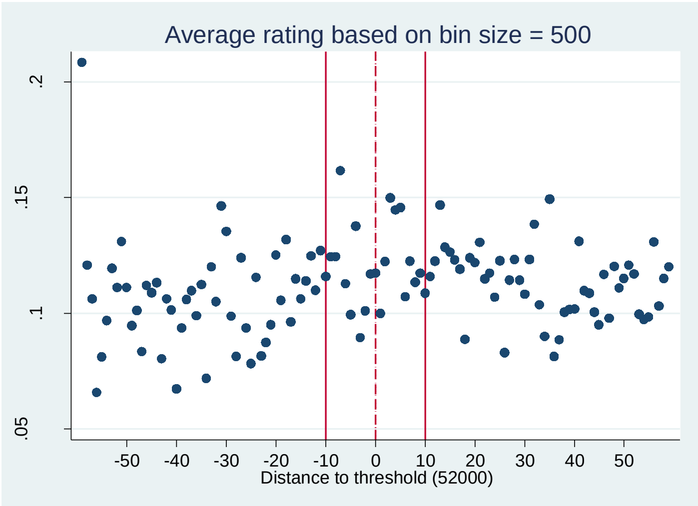
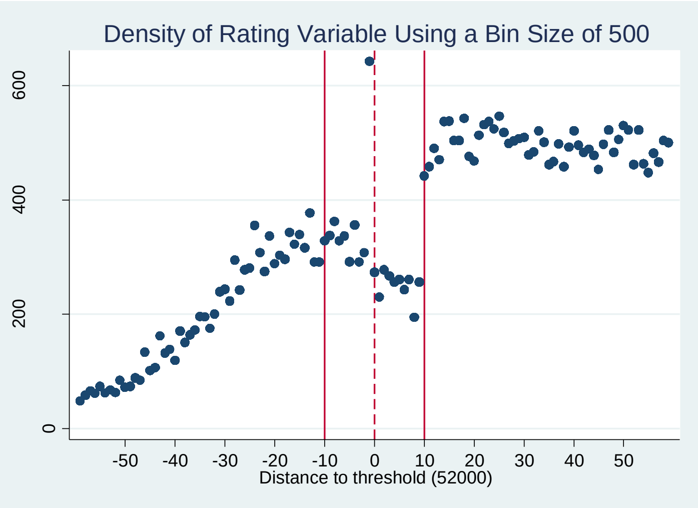


Figure 6: (Data set 2) – Density of rating variable. The solid lines refer 5000 poverty score neighborhood around cut-off. The figure demonstrates continuity of the density in the local area.



Appendix B

Table B1

Step 1 – Bin size selection criteria, F–test

Bin size	Restricted R^2	Unrestricted R^2	# of bins	Observations	F value
10000	0.0007	0.0009	19	105377	1.11
5000	0.0009	0.0013	39	105377	1.08
2000	0.0013	0.0023	99	105377	1.07
1000	0.0023	0.0043	199	105377	1.06
500*	**0.0043**	**0.0081**	**399**	**105377**	**1.01***
200	0.0115	0.0213	999	105377	1
100	0.0213	0.0411	1999	105377	1
50	0.0249	---	3999	105377	---

Table B2

Step 2 – Model specification, F–test

Model specification	no covariates	Estimate	St. Error	t value	F - Value
Linear	model 1	0.00368	0.0041	0.89	1.012
Linear interaction*	**model 2**	**0.00917**	**0.0048**	**1.92**	**0.904***
Quadratic	model 3	0.00710	0.0050	1.41	0.904
Quadratic interaction	model 4	0.00942	0.0068	1.38	0.904
Cubic	model 5	0.00629	0.0050	1.24	0.905
Cubic interaction	model 6	0.01033	0.0089	1.16	0.904
4th degree	model 7	0.00535	0.0059	0.91	0.903
4th degree interaction	model 8	0.01823	0.0109	1.66	0.888
5th degree	model 9	0.00751	0.0063	1.19	0.903
5th degree interaction	model 10	0.01615	0.0114	1.41	0.904
	with covariates				
Linear	model 1	0.00308	0.0041	0.75	1.06
Linear interaction*	**model 2**	**0.00775**	**0.0046**	**1.69**	**0.89***
Quadratic	model 3	0.00554	0.0050	1.10	0.90
Quadratic interaction	model 4	0.00841	0.0068	1.24	0.89
Cubic	model 5	0.00486	0.0051	0.96	0.90
Cubic interaction	model 6	0.00915	0.0089	1.03	0.89
4th degree	model 7	0.00408	0.0059	0.69	0.90
4th degree interaction	model 8	0.01663	0.0109	1.52	0.90
5th degree	model 9	0.00637	0.0063	1.01	0.90
5th degree interaction	model 10	0.01460	0.0114	1.28	0.90

Table B3

Step 3 – Robustness checks, comparisons of estimates under three levels of outermost point dropouts

Dropping outliers	Treatment estimates	Standard Errors	t value
Dropping outermost 1%	0.009	0.005	1.80
with covariates	0.008	0.005	1.52
Dropping outermost 5%	0.006	0.005	1.08
with covariates	0.005	0.005	0.89
Dropping outermost 10%	0.008	0.006	1.35
with covariates	0.007	0.006	1.21

Table B4

Step 1 – Bin size selection criteria, F–test

Bin size	Restricted R^2	Unrestricted R^2	# of bins	Observations	F value
10000	0.0008	0.0012	19	75532	1.59
5000	0.0012	0.0018	39	75532	1.16
2000	0.0019	0.0034	99	75532	1.14
1000	0.0034	0.0061	199	75532	1.03
500*	**0.0061**	**0.0113**	**399**	**75532**	**0.99***
200	0.0142	0.0265	999	75532	0.94
100	0.0265	0.0502	1999	75532	0.92
50	0.0502	---	3999	75532	---

Table B5

Step 2 – Model specification, F–test

Model specification	no covariates	Estimate	St. Error	t value	F value
Linear	model 1	0.0037	0.0040	0.92	1.06
Linear interaction	model 2	0.0121	0.0055	2.19	1.04
Quadratic	model 3	0.0021	0.0054	0.39	1.00
Quadratic interaction*	**model 4**	**0.0135**	**0.0071**	**1.87**	**1.00***
Cubic	model 5	0.0027	0.0063	0.44	1.00
Cubic interaction	model 6	0.0010	0.0101	0.1	1.00
4th degree	model 7	0.0017	0.0063	0.27	1.00
4th degree interaction	model 8	-0.0044	0.0124	-0.35	1.00
5th degree	model 9	0.0048	0.0071	0.68	1.00
5th degree interaction	model 10	-0.0301	0.0147	-2.05	0.98
	with covariates				
Linear	model 1	0.0037	0.0040	0.93	1.06
Linear interaction	model 2	0.0118	0.0055	2.14	1.04
Quadratic	model 3	-0.0021	0.0054	-0.38	1.01
Quadratic interaction*	**model 4**	**0.0092**	**0.0078**	**1.17**	**1.00**
Cubic	model 5	0.0027	0.0063	0.44	1.01
Cubic interaction	model 6	0.0010	0.0101	0.1	1.01
4th degree	model 7	0.0017	0.0063	0.27	1.02
4th degree interaction	model 8	-0.0041	0.0124	-0.33	1.01
5th degree	model 9	0.0049	0.0071	0.68	1.01
5th degree interaction	model 10	-0.0172	0.0130	-1.32	1.00

Table B6

Step 3 – Robustness checks, comparisons of estimates under three levels of outermost point dropouts

	Treatment estimates	Standard Errors	t value
Dropping outermost 1%	0.014	0.006	2.30
with covariates	0.013	0.006	2.23
Dropping outermost 5%	0.012	0.007	1.67
with covariates	0.012	0.007	1.64
Dropping outermost 10%	0.016	0.010	1.60
with covariates	0.016	0.010	1.60

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