Appendix 1. Contrast with Evans (2012) and Replication

As mentioned above, Evans (2012) also examines SMART Grants using data from Ohio universities. He focuses on students who entered college in 2006-2007 and follows them through spring 2010. Using a similar regression discontinuity design on Ohio data, he finds no evidence of an impact of SMART Grants on students majoring in STEM fields.

Several of our results lend insight into why our estimates differ. Primarily, Evans has less statistical power that the current paper and is trying to measure an impact that is smaller than what we are measuring. First, our analysis measures the impact of SMART Grants on all eligible majors while Evans only considered STEM majors. Since it appears that language majors make up about 20 percent of the effect, he is trying to measure a smaller value than we are. Second, Evans' sample is smaller than ours since he restricts it only to students who enter college in 2006-2010 while we use all students who are juniors or seniors during the lifetime of the grant. That is, our analysis includes all students who Evans would include and also students who start earlier and progress more slowly to graduation or who start later and progress more quickly. Third, Evans does not have data for the last year that the SMART Grant program existed. Our analysis suggests that there was an increasing impact of the program over time, meaning that Evans is trying to measure a smaller impact that what we measure in our analysis. Of course, it is possible that the measured difference is simply due to geographic heterogeneity, and the program had a larger impact in Texas than in Ohio. This would be consistent with the measured differences we observe between public universities in Texas and at BYU. However, the Texas and Ohio data both include primarily large public universities that are similar in observable characteristics, making it seem more likely that we would observe similar effects in each sample.

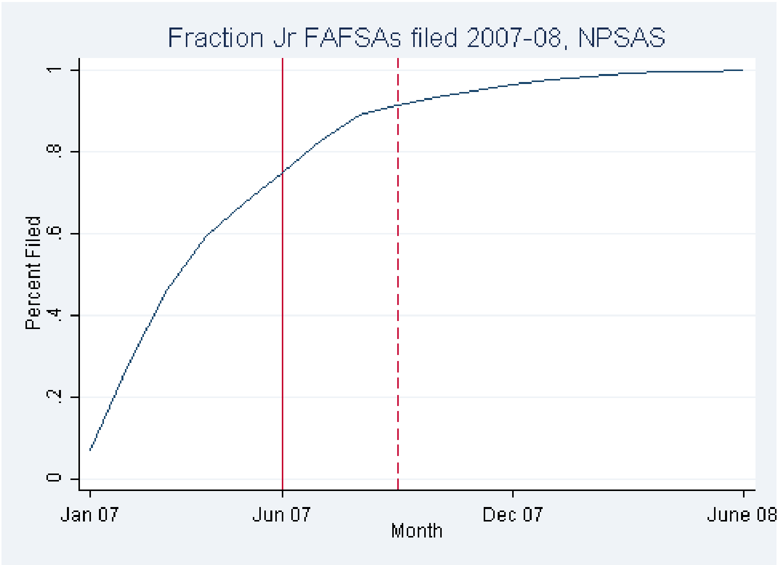
An additional relative strength of our data set is we observe grant receipt directly and can measure the size of the discontinuity in grant receipt. The final difference is that we are able to examine the years prior to the grant and one year after the grant as a placebo test. This provides a valuable falsification test that allows us to attribute our estimates to the grant program as opposed to chance or effects from the Pell Grant program.

To test if Evans' data restrictions and outcome variable are sufficient to account for his lack of a measured impact, we restrict our sample in the same way, only including students entering college in 2006-2007 and removing all data after spring 2010, and measure the impact of SMART Grants on STEM majors. These replication results, which are found in the online appendix Table A1, fail to be statistically significant much like Evans (2012), although the magnitude of the estimates are similar to those in our main analysis.[27] We believe that this is evidence that a significant portion of the difference between Evans' and our estimates is purely due to the empirical issues described above. We can't measure, however, to what degree, if any, heterogeneity accounts for the remaining measured difference.

Appendix Tables and Figures.

Figure A1

Timing of FAFSA Submission



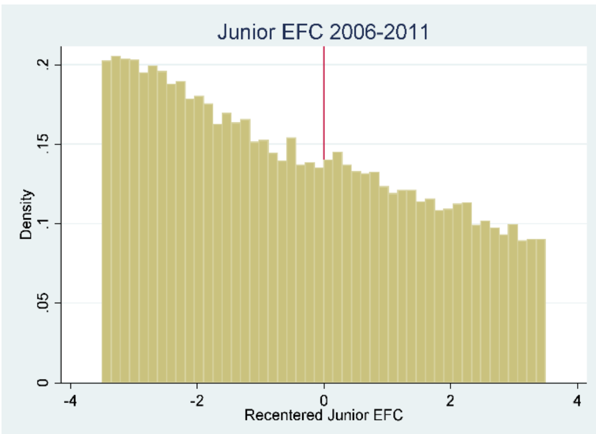
This figure represents the cumulative density function of FAFSA filing for juniors in the 2007-08 NPSAS. The school year starts in August 2007 and is represented by the dashed line. The vertical line at June 07 is to highlight that the bulk of FAFSA submissions occurs several months prior to the school year starting.

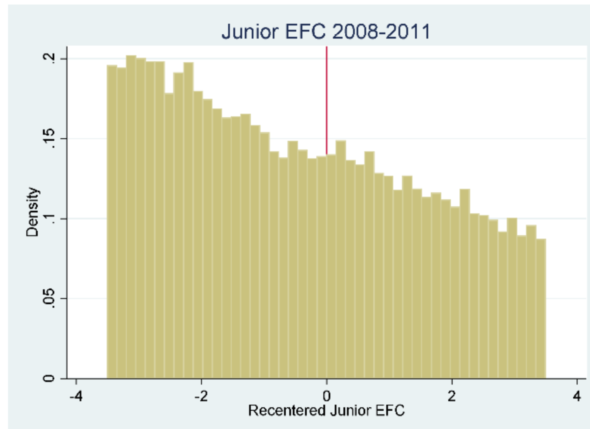
Figure A2

Density of EFC

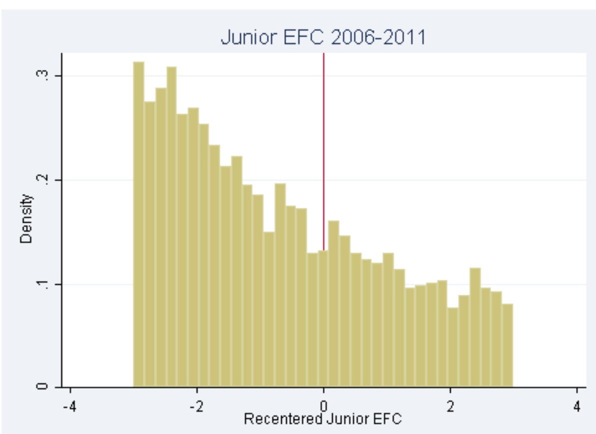
2006-07 to 2010-11 | 2008-09 to 2010-11

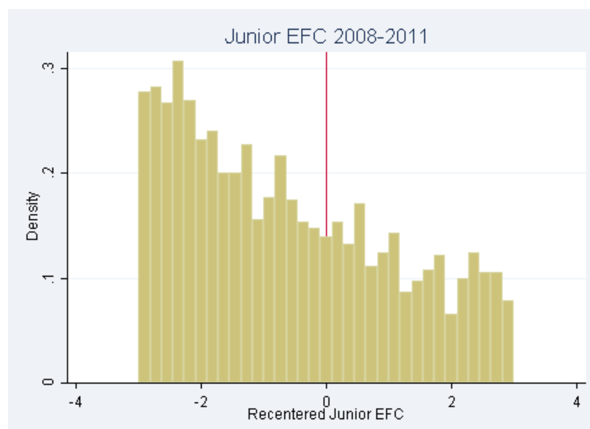
Texas





BYU





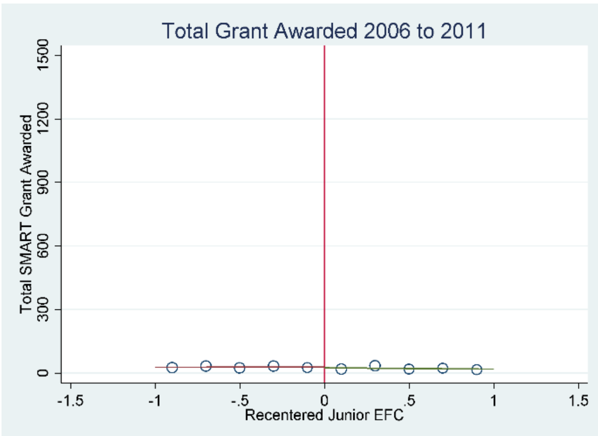
These figures depict the density of recentered EFC in the first semester a student is classified as a junior. EFC is recentered so that SMART eligibility occurs to the left of 0 and EFC is divided by 1,000.

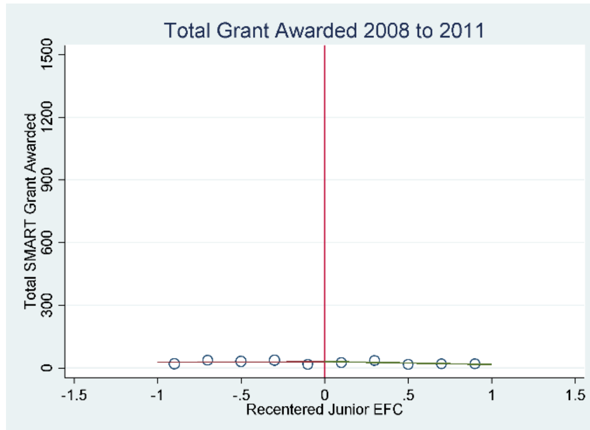
Figure A3

Total SMART Grant

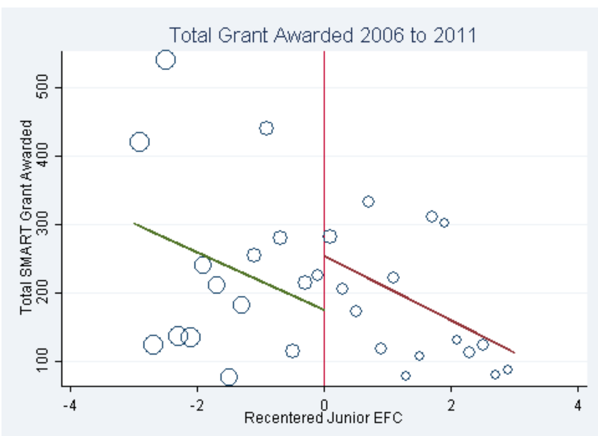
Non SMART Majors

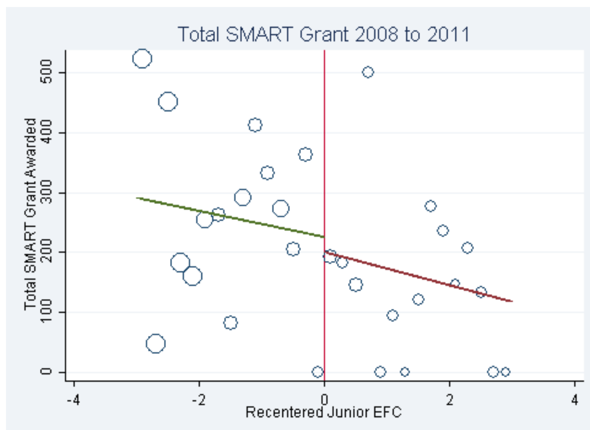
Texas





BYU





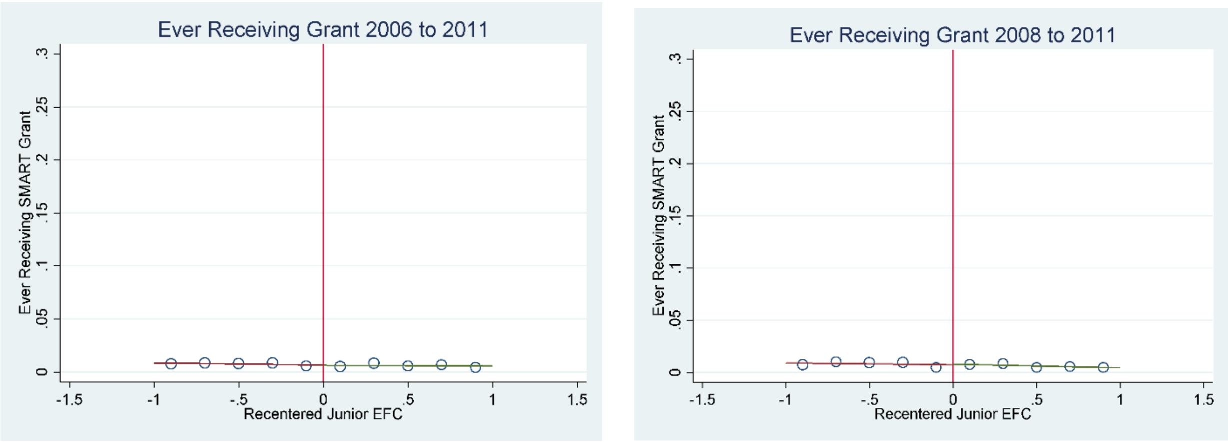
The average amount of the SMART Grants received is plotted against recentered junior EFC for students not declared in SMART majors at the beginning of their junior year. Each dot represents the average for students in a bin of 200 EFC. EFC is recentered so that SMART eligibility occurs to the left of 0 and EFC is divided by 1,000. The size of the dot is proportional to the number of observations included in the average. The lines represent linear predictions allowed to vary on each side of the cutoff. The bandwidth used at Texas 1.0 and the bandwidth at BYU is 2.0.

Figure A4

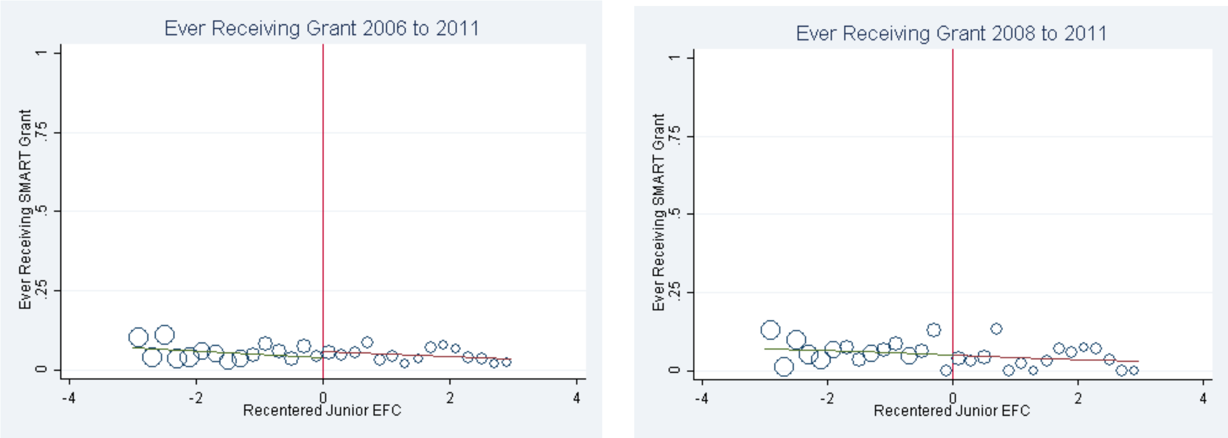
Figure Ever SMART Grant

Non SMART Majors

Texas



BYU



The probability of ever receiving a SMART Grant is plotted against recentered junior EFC for students not declared in SMART majors at the beginning of their junior year. Each dot represents the average for students in a bin of 200 EFC. EFC is recentered so that SMART eligibility occurs to the left of 0 and EFC is divided by 1,000. The size of the dot is proportional to the number of observations included in the average. The lines represent linear predictions allowed to vary on each side of the cutoff. The bandwidth used at Texas 1.0 and the bandwidth at BYU is 2.0.

Table A1

Evans Replication

	Ever SMART	SMART Amount	STEM Major	Senior Major	Degree
Discontinuity	0.0263*	87.44	0.0407	0.0407	0.0216
	(0.0159)	(54.80)	(0.0274)	(0.0267)	(0.0246)
Observations	3281	6736	3281	3281	3281

This table tries to replicate the sample conditions of Evans (2012) using the Texas data. Data from before the 2010 school year is used and only students who entered in 2006-07 or 2007-08 school year are included. Standard errors are in parenthesis and *** p<.01, ** p<.05, and * p<.1

Table A2

Bandwidth Sensitivity

Texas

Junior SMART Major

Bandwidth	0.5	0.6	0.7	0.8	0.9	1	1.1	1.2	1.3	1.4
Discontinuity	0.0464**	0.0470**	0.0447**	0.0362**	0.0350**	0.0324**	0.0230*	0.0265**	0.0234*	0.0184
	(0.0205)	(0.0189)	(0.0175)	(0.0163)	(0.0153)	(0.0145)	(0.0140)	(0.0134)	(0.0128)	(0.0123)
Observations	5641	6743	7802	8946	10030	11161	12242	13347	14498	15645

Senior SMART Major

Bandwidth	0.5	0.6	0.7	0.8	0.9	1	1.1	1.2	1.3	1.4
Discontinuity	0.0461**	0.0488**	0.0501***	0.0402**	0.0375**	0.0331**	0.0237	0.0273*	0.0235*	0.0205
	(0.0222)	(0.0203)	(0.0189)	(0.0175)	(0.0165)	(0.0156)	(0.0150)	(0.0144)	(0.0138)	(0.0132)
Observations	4884	5817	6719	7698	8607	9591	10505	11457	12440	13430

Junior SMART Major, Quadratic

	2.5	3	3.5	4
Discontinuity	0.0255*	0.0169	0.0110	0.0220**
	(0.0136)	(0.0125)	(0.0116)	(0.0109)
Observations	28351	34162	39933	46245

Senior SMART Major, Quadratic

	2.5	3	3.5	4
Discontinuity	0.0269**	0.0187	0.0146	0.0216**
	(0.0128)	(0.0117)	(0.0108)	(0.0101)
Observations	28351	34162	39933	46245

	Degree, Quadratic			
	2.5	3	3.5	4
Discontinuity	0.000317	-0.00195	-0.00276	0.00611
	(0.00975)	(0.00892)	(0.00829)	(0.00779)
Observations	28351	34162	39933	46245

BYU

	Junior SMART Major									
	1.5	1.6	1.7	1.8	1.9	2	2.1	2.2	2.3	2.4
Discontinuity	0.131**	0.132**	0.103*	0.113**	0.102**	0.102**	0.108**	0.112**	0.110**	0.105**
	(0.0575)	(0.0552)	(0.0541)	(0.0528)	(0.0504)	(0.0493)	(0.0480)	(0.0466)	(0.0455)	(0.0445)
Observations	958	1,026	1,082	1,145	1,236	1,297	1,363	1,448	1,524	1,604

	Senior SMART Major									
	1.5	1.6	1.7	1.8	1.9	2	2.1	2.2	2.3	2.4
Discontinuity	0.147***	0.124**	0.0857*	0.102**	0.0950**	0.101**	0.109**	0.109**	0.110**	0.0983**
	(0.0546)	(0.0527)	(0.0517)	(0.0502)	(0.0479)	(0.0468)	(0.0457)	(0.0442)	(0.0433)	(0.0424)
Observations	958	1,026	1,082	1,145	1,236	1,297	1,363	1,448	1,524	1,604

	Junior SMART Major, Quadratic					Senior SMART Major, Quadratic				
	2	2.5	3	3.5	4	2	2.5	3	3.5	4
Discontinuity	0.155**	0.153**	0.125**	0.129**	0.143***	0.168**	0.150**	0.126**	0.126**	0.136***
	(0.0754)	(0.0665)	(0.0600)	(0.0547)	(0.0512)	(0.0715)	(0.0634)	(0.0574)	(0.0525)	(0.0491)
Observations	1297	1685	2082	2519	2972	1297	1685	2082	2519	2972

	Degree, Quadratic				
	2	2.5	3	3.5	4
Discontinuity	0.106*	0.105**	0.0975**	0.103**	0.0807**
	(0.0542)	(0.0499)	(0.0455)	(0.0418)	(0.0394)
Observations	1297	1685	2082	2519	2972

This table estimates the discontinuity by varying the bandwidth or using a quadratic running variable allowed to vary on each side of the cutoff. Students from 2008-09 to 2010-11 are used in estimation. Standard errors are in parenthesis and *** p<.01, ** p<.05, and * p<.1

[27] We use the optimal bandwidth in the Texas data using the data restrictions described for the replication exercise because bandwidth selection is dependent on the data set used.