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# The Effect of Federal Grants on Student Outcomes

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## Abstract

Federal financial aid depends on a student’s Expected Family Contribution (EFC)—the higher her EFC, the less aid a student receives. We estimate the effect of increasing federal aid on student outcomes by leveraging an increase in the income threshold for an “automatic zero EFC,” which qualifies students for the most generous federal aid. We find little evidence that expanding eligibility for an automatic zero EFC affected student outcomes. We argue this may be due to the volatility of federal aid from year to year and highlight this as an important dimension for future research.

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# 1 Introduction

This paper estimates the effect of federal financial aid on student outcomes. Federal financial aid is awarded according to a complicated formula that depends on a large number of factors. This formula produces a measure called the Expected Family Contribution (EFC) that represents the federal government’s estimate of how much a student’s family can be expected to contribute toward her education. The lower a student’s EFC, the more financial aid she is eligible for. For students with family income below a certain threshold, the government assigns them an “automatic zero EFC,” thereby making them eligible for the most generous federal financial aid package. For the 2007–2008 school year, the auto-zero-EFC threshold was set at \$20,000; thus, EFC’s for students below this income threshold were automatically set to zero. The threshold was then raised to \$30,000 for the 2009–2010 school year and again to \$31,000 for the 2011–2012 school year. We employ a difference-in-differences strategy to exploit this policy change and estimate the effect of increased federal aid on student outcomes. As expected, we find that, among students with incomes between \$20,000 and \$31,000, raising the auto-zero-EFC threshold increased federal grants by \$1,121 per year. We also find some crowd out of federal student loans as these same students borrowed \$556 less.<sup>1</sup> Despite these pronounced effects on student aid, we do not find a significant effect on any other student outcome measure including institutional aid, enrollment intensity, GPA, working while in school, or choosing a STEM major.

We are not the first to estimate the effect of federal grants on student outcomes. In a review of the literature, Deming and Dynarski (2010) report mixed findings on the effect of Pell grants on student outcomes. Other forms of grant aid such as Social Security benefits (Dynarski, 2003), veterans benefits (Bound and Turner, 2002), and state-based merit grants (Dynarski, 2000; Kane, 2007) show more promising results. Our paper is most closely related to Denning et al. (2019), which leverages the discontinuity in federal aid introduced by the auto-zero-EFC threshold. Using data from Texas, Denning et al. (2019) exploit the discontinuity in Pell grants at the auto-zero-EFC threshold to estimate the effect of Pell grants, and they find positive effects of receiving an automatic zero EFC on college completion and wages. In contrast, Eng and Matsudaira (2021) replicate Denning et al. (2019)’s empirical strategy using administrative data on the universe of students who received federal aid, and they find smaller and less robust effects on completion and wages. Our paper differs from both in several ways. First, like Eng

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<sup>1</sup>Some of this crowd out may be mechanical, due to the federal financial aid formulas themselves.

and Matsudaira (2021) but unlike Denning et al. (2019), we use nationally representative data. Second, both papers focus on the discontinuity imposed by the auto-zero-EFC income threshold, whereas we exploit a policy change in that threshold. Third, Denning et al. (2019) are missing data on several criteria for an auto-zero-EFC, which forces them to adopt a fuzzy RD design, while our data include all the inputs used in federal aid calculations. And fourth, Denning et al. (2019)'s data allow them to look at both enrollment effects and labor market outcomes. Like Eng and Matsudaira (2021), our data sample students who are already enrolled in college, so we are restricted to look at financial and academic outcomes after first enrollment.

While these differences could explain the differences in our findings with those of Denning et al. (2019), an alternative explanation may lie in the TEXAS (Towards EXcellence, Access and Success) Grant, which awards students in Texas a grant up to the statewide average of tuition and fees. Denning et al. (2019) find that receiving an auto-zero-EFC raises the probability of receiving a TEXAS Grant. Crucially, once a student receives a TEXAS Grant, she is eligible to continue receiving the grant for up to five years, which adds a great degree of predictability to her financial aid. Thus, not only does a zero EFC crowd in grant dollars, it makes those dollars more predictable going forward. In contrast, it turns out that federal financial aid is surprisingly volatile from year to year. Among students in 2011–2012 with income between \$20,000 and \$31,000—and who were therefore eligible for an automatic zero EFC—nearly half of them failed to qualify for a zero EFC the next year. Given the uncertainty over future financial aid, it is not surprising that a one-time increase in aid has a much smaller effect on educational investments than a guaranteed flow of aid that will last for several years. Thus, our results highlight the importance of a neglected dimension of financial aid—the stability and predictability of aid over a student's college career.

## 2 Policy Change

Federal financial aid in the United States is determined by a complicated nonlinear formula that takes into account income, assets, family size, and other factors to calculate an Expected Family Contribution (EFC). Students who apply for federal aid must complete the Free Application for Federal Student Aid (FAFSA) which contains over 100 questions, many of which request detailed financial information about the student and her parents. To ease the burden of completing the FAFSA for lower income students, students can qualify for a simplified EFC formula if they pass

a “Simplified Need Test” (SNT), the most important element of which is that income be below \$50,000.<sup>2</sup> Among students who pass the SNT, those with incomes below the auto-zero-EFC threshold receive an automatic zero EFC, which qualifies them for the most generous federal aid available. While some students who do not receive an automatic zero EFC do end up receiving a zero EFC anyway, in general their EFC’s tend to be higher, thereby reducing the federal aid they receive. Figure 1 plots mean EFC by income for those who passed the SNT. For incomes below the auto-zero-EFC threshold, the mean EFC is zero. But above the threshold, the mean EFC immediately jumps by about \$1,000 and rises gradually with income thereafter.

The auto-zero-EFC threshold was raised from \$20,000 to \$30,000 for the 2009-2010 school year and again to \$31,000 two years later. Figure 1 plots mean EFC in \$1,000 income bins for the 2007-2008 school year and the 2011-2012 school year. As figure 1 illustrates, the increase in the auto-zero-EFC threshold shifted the entire EFC schedule to the right, which lowered the mean EFC’s for everyone except for those below \$20,000 who were already at a zero EFC. Students just above the old threshold of \$20,000 saw a drop in their EFC’s of about \$1,000 while those just below the new threshold of \$31,000 saw their EFC’s fall by over \$2,000.

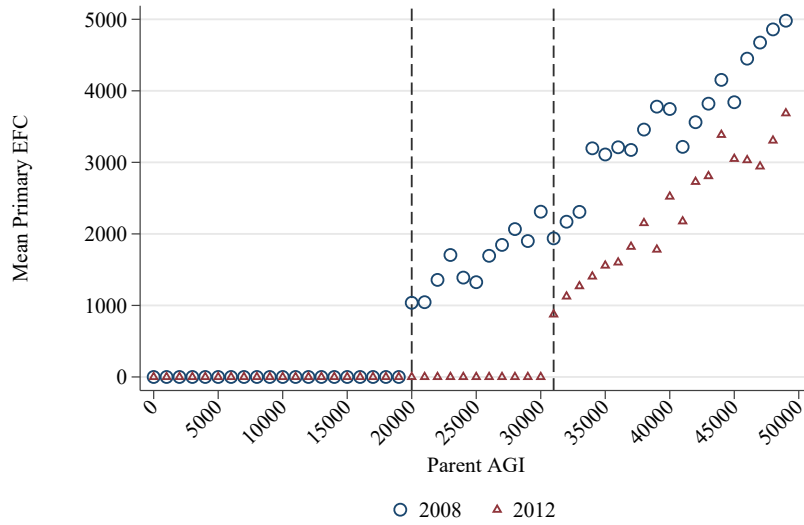
The change in the auto-zero-EFC threshold translated into a pronounced increase in federal Title IV grants. Figure 2 plots mean Title IV grants received in \$1,000 income bins for the 2007-2008 school year and the 2011-2012 school year. For students below \$20,000 of income, grants did not rise because those students were already receiving the most generous federal aid available. But for students just above \$20,000, grants rose by nearly \$1,000 while for students closer to \$30,000 grants rose by \$1,500.

### 3 Data

Our data come from the National Postsecondary Student Aid Study (NPSAS) and Beginning Postsecondary Students (BPS). NPSAS is a large, nationally representative cross-section of college students in the United States. The survey is conducted about every four years, and provides a detailed picture of how students finance their education. BPS is drawn from first-time freshmen in NPSAS and follows them for six years. For this paper, we used the 2008

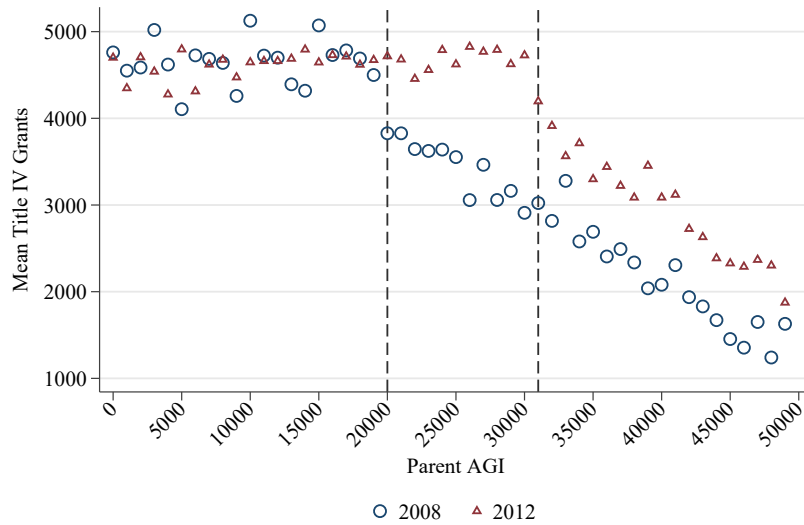
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<sup>2</sup>In addition, the SNT requires that either 1) at least one member of the student’s household must have received benefits from any of the designated means tested federal benefit programs, OR 2) the student’s parents were eligible to file IRS form 1040A or 1040EZ or were not required to file any income tax return.



SOURCE: U.S. Department of Education, National Center for Education Statistics, National Postsecondary Student Aid Study, 2008 & 2012.

Figure 1: This figure plots mean EFC in \$1,000 income bins for the 2007-2008 school year and the 2011-2012 school year. The vertical dashed lines indicate the auto-zero-EFC thresholds for each year.



SOURCE: U.S. Department of Education, National Center for Education Statistics, National Postsecondary Student Aid Study, 2008 & 2012.

Figure 2: This figure plots mean Title IV grants received in \$1,000 income bins for the 2007-2008 school year and the 2011-2012 school year. The vertical dashed lines indicate the auto-zero-EFC thresholds for each year.

and 2012 waves of NPSAS (covering the 2007-2008 and 2011-2012 school years) and the 2004-2009 and 2012-2017 panels of BPS. Both NPSAS and BPS contain detailed data on income and financial aid, including a student’s EFC. The NPSAS data sample has the advantage of being both larger and closer in proximity to the policy change, while the BPS sample allows us to follow students over time. Thus, we use NPSAS to estimate short run effects and BPS to estimate longer run effects.

Table 1 reports summary statistics for the NPSAS sample. The sample is restricted to students who qualify for the Simplified Needs Test, which means their parents’ income is below \$50,000. They are predominantly enrolled at public colleges. Due to a change in survey design, NPSAS sampled many more students at two-year and for-profit colleges in 2012. Thus, in our regression analyses we use sampling weights and control for institution level and type. EFC’s are lower, and federal grants higher, in 2012 due to the shift in the EFC schedule documented in Figure 1.

Table 2 reports summary statistics for the BPS sample. Unlike the NPSAS sample, this sample is restricted to freshmen and is therefore smaller. But it does follow students for six years, which allows us to look at a variety of longer run outcomes such as cumulative student borrowing, cumulative enrollment, and six-year completion. As with NPSAS, a change in survey design increased the number of students at for-profit colleges in 2012, so we use sample weights and control for institution level and type.

## 4 Empirical Strategy

We leverage the change in the income threshold for an automatic zero EFC by using a difference-in-differences strategy. We compare students with an income between \$10k-\$20k (just below the original threshold) with those with incomes between \$20k-\$31k. Students in the first group (“Below”) were eligible for an automatic zero EFC in both 2008 and 2012 while students in the second group (“Above”) were only eligible in 2012, after the threshold was raised. Our regression specification is

$$y_{it} = \beta_1 \mathbf{1}\{\text{Above}\} + \beta_2 \mathbf{1}\{\text{After Change}\} + \beta_3 \mathbf{1}\{\text{Above}\} \times \mathbf{1}\{\text{After Change}\} + X_i \delta + u_{it} \quad (1)$$

Table 1: Descriptive Statistics, National Postsecondary Student Aid Study (unweighted)

	Year	
	2008	2012
Number of Observations	7,460	8,180
Mean Expected Family Contribution (EFC)	\$1,596	\$625
Percent with \0 EFC	46.2%	73.9%
Adjusted Gross Income (AGI)		
Less than \10,000	11.7%	11.1%
\\$10,000 to \\$20,000	26.5%	28.2%
\\$20,000 to \\$31,000	28.7%	31.0%
\\$31,000 to \\$50,000	33.2%	29.8%
Mean Age	20.1	19.2
Percent Female	58.8%	54.9%
Mean ACT Score	20.3	19.5
Mean Title IV Grant Amount	\$3,510	\$4,205
Mean Federal Loan Amount	\$3,653	\$5,311
Institution Level		
4-year	72.0%	58.3%
2-year	28.0%	41.7%
Institution Type		
Public	68.4%	55.7%
Private not-for-profit	23.6%	14.2%
Private for-profit	8.1%	30.1%

Income is less than \50,000 in our sample, in keeping with the criteria of the Simplified Needs Test. ACT scores come from NPSAS variable TEACTDER. EFCs from 2008 come from NPSAS variable C08196. Degree lengths come from NPSAS variable LEVEL. Institution types are derived from NPSAS variable AIDSECT. Title IV grant amount is the sum of contributions from Pell grants, Academic Competitiveness Grants (ACGs), National Science and Mathematics Access to Retain Talent (SMART) grants, and Federal Supplemental Education Opportunity Grants (FSEOGs). Sample counts were rounded to the nearest 10. No sample weights were used.



Table 2: Descriptive Statistics, Beginning Postsecondary Students (unweighted)

	Year	
	2004	2012
Number of Observations	1,150	2,490
Mean Expected Family Contribution (EFC)	\$1,524	\$536
Percent with \ \$0 EFC	41.4%	74.8%
Adjusted Gross Income (AGI)		
Less than \ \$10,000	16.4%	13.6%
\ \$10,000 to \ \$20,000	25.8%	28.6%
\ \$20,000 to \ \$31,000	28.7%	28.3%
\ \$31,000 to \ \$50,000	29.1%	29.5%
Percent Female	59.4%	60.1%
Mean ACT Score	19.5	19.6
Mean Title IV Grant Amount	\$2,672	\$4,406
Mean Federal Loan Amount	\$2,525	\$4,931
Institution Level		
4-year	61.2%	59.2%
2-year	38.8%	40.8%
Institution Type		
Public	68.8%	59.4%
Private not-for-profit	26.6%	19.4%
Private for-profit	4.6%	21.2%

Income is less than \ \$50,000 in our sample, in keeping with the criteria of the Simplified Needs Test. Title IV grant amount is the sum of contributions from Pell grants, Academic Competitiveness Grants (ACGs), National Science and Mathematics Access to Retain Talent (SMART) grants, and Federal Supplemental Education Opportunity Grants (FSEOGs). All counts were rounded to the nearest 10. No sample weights were used.

where  $\beta_3$  is the parameter of interest. We also include the following controls ( $X_i$ ): student’s race, gender, test score, grade level, and household size; parents’ education; state fixed effects; and college level and type.<sup>3</sup> Our identification strategy relies on the standard parallel trends assumption. Specifically, we assume that the trends over time for the Above and Below groups would be the same in the absence of the policy change.

We can interpret  $\beta_3$  from equation (1) in two ways. If we consider treatment to be whether a student receives an automatic zero EFC, then  $\beta_3$  represents the average treatment effect on the treated. Instead, if we consider treatment to be the size of a student’s grants, then  $\beta_3$  represents an “intention-to-treat” effect, which would need to be divided by the “first stage” effect of receiving an automatic zero EFC on grants in order to arrive at the local average treatment effect of grants on student outcomes. In the next section, we report  $\beta_3$  for a variety of outcome variables. We do find that  $\beta_3$  is large and very significant when the outcome variable is Title IV grants, implying a strong “first stage.” But since we do not find significant values for  $\beta_3$  for most other outcomes, we do not find significant effects of grants on student outcomes either.

## 5 Results

Table 3 reports estimates of the regression specification in (1) for a variety of outcomes using the NPSAS data. As expected, receiving an automatic zero EFC significantly increases a student’s Title IV grants by \$1,253, and this increased grant aid appears to crowd out \$453 of student borrowing. Total Title IV aid (grants, loans, and work-study) rises by \$820. However, we do not find a significant effect on any other student outcome. Institutional grants are unaffected. Enrollment intensity appears to be unaffected, whether measured by the number of months enrolled full time or by whether the student works while enrolled.<sup>4</sup> Student grades are unaffected as is whether the student chooses a major in Science, Technology, Engineering, or Math (STEM).

Table 4 reports results using the BPS data. Although BPS is smaller, it does allow us to look at longer run outcomes. Just as in Table 3, we find that an auto-zero-EFC increases grants while lowering borrowing somewhat. But we do not find a significant effect on cumulative borrowing after six years or receiving a Bachelor’s degree, although the latter estimate is somewhat noisy.

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<sup>3</sup>Our findings are not sensitive to including these controls.

<sup>4</sup>We do not have data on number of credits earned.

Table 3: Short Run Effects of Receiving an Auto-Zero-EFC on Student Outcomes (NPSAS)

	Title IV Grants	Title IV Loans	Total Title IV Aid	Institutional Grant Amount	Months Enrolled Full-Time	Whether Student Works	Job-Hours per Week	Grade Point Average	Whether Student is a STEM Major
AGI>\$20k	-1295.9 (60.90)***	435.0 (110.0)***	-879.6 (134.8)***	18.56 (124.3)	-0.208 (0.0704)**	0.0196 (0.0145)	0.625 (0.437)	1.185 (2.145)	0.00174 (0.0127)
2012	344.6 (55.55)***	1455.9 (140.9)***	1710.3 (165.3)***	16.35 (135.2)	0.00387 (0.0807)	-0.106 (0.0157)***	-1.592 (0.475)***	-10.03 (2.549)***	-0.0710 (0.0127)***
AGI>\$20k * 2012	1252.5 (76.44)***	-452.8 (183.8)*	819.6 (215.1)***	143.2 (171.8)	0.184 (0.104)	0.00225 (0.0202)	-0.0724 (0.614)	1.502 (3.247)	-0.00722 (0.0164)
$R^2$	0.267	0.317	0.343	0.437	0.091	0.081	0.071	0.144	0.165
Mean	3873.3	4520.5	8702.4	2433.9	8.631	0.588	14.28	278.7	0.218
Controls	X	X	X	X	X	X	X	X	X
State fixed effects	X	X	X	X	X	X	X	X	X
Obs	8960	8960	8960	8960	8960	8960	8960	8960	8960

Heteroskedasticity robust standard errors are in parentheses. The sample is limited to students with parent income between \$10k-\$31k. The difference-in-differences estimates are in the third row. Grade point average is scaled so that 4.00 corresponds to a 4.00 GPA. The mean of the outcome for students with income between \$20k-\$31k in 2012 is reported in the lower panel. Sample weights were used in all regressions.

SOURCE: U.S. Department of Education, National Center for Education Statistics, National Postsecondary Student Aid Study. 2008 & 2012.

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$

We do find a significant effect on total full-time-equivalent months enrolled at the six-year mark.<sup>5</sup> However, the point estimate is relatively small, amounting to less than a semester’s worth of additional enrollment over six years.

Figure 3 presents the difference-in-differences estimates across both short run outcomes (in NPSAS) and longer run outcomes (in BPS). To make these estimates comparable, the two subfigures on the left divide the estimates by the mean of the outcome for students with income between \$20k-\$31k in 2012. Thus, the estimates are presented as a percentage change relative to the mean. The two subfigures on the right divide the estimates by the standard deviation of the outcome for students with income between \$20k-\$31k in 2012. This measure is also known as Cohen’s *d*, and it measures a treatment effect in standard deviations of the outcome.<sup>6</sup> The effect on Title IV grants stands out from the others with an auto-zero-EFC raising grants by over 25 percent of the mean or nearly 0.8 standard deviations. For outcomes like short run enrollment, working while enrolled, and GPA, our confidence intervals rule out effects larger than 10 percent of the mean. And, aside from Title IV Grants, we can rule out effect sizes larger than 0.2 standard deviations for any short run outcome. For longer run outcomes, the confidence intervals are less informative, but point estimates are all within 10 percent of the mean and 0.2 standard deviations. The one exception is the total number of full-time equivalent months enrolled over six years. We find a roughly 10 percent increase in months enrolled which corresponds to about 0.2 standard deviations or about three additional months of enrollment over six years.

## 6 Comparing Results with Denning et al. (2019)

Our setting is similar to that of Denning et al. (2019), so in this section we compare our findings with theirs. Before doing so, we highlight the differences between the two papers. First, Denning et al. (2019) use data from a single state (Texas) while we use nationally representative data. Second, they focus on the discontinuity imposed by the auto-zero-EFC income threshold, whereas we exploit a policy change in that threshold. Third, they are missing data on several criteria for an auto-zero-EFC, which forces them to adopt a fuzzy RD design, while our data include all the inputs used in federal aid calculations. And fourth, Denning et al. (2019)’s data allow them

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<sup>5</sup>We do not have data on the cumulative number of credits earned.

<sup>6</sup>An effect size of 0.2 is often considered “small,” 0.5 is considered “medium,” and 0.8 is considered “large.”

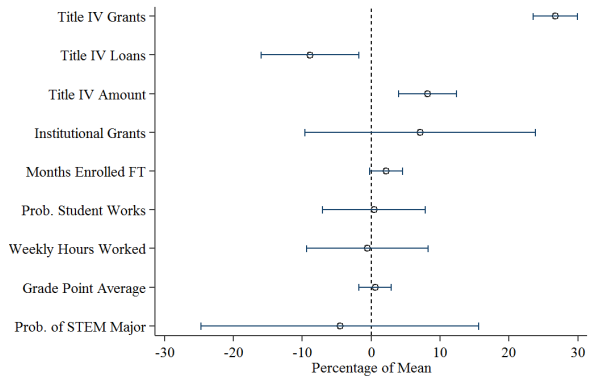
Table 4: Longer Run Effects of Receiving an Auto-Zero EFC on Student Outcomes (BPS)

	Title IV Grants	Title IV Loans	Total Title IV Aid	Institutional Grant Amount	Cumul. Title IV Loans (6 Years)	Bach. Deg. (6 Years)	FTE Months (3 Years)	FTE Months (6 Years)
AGI>\$20k	-1062.3 (111.4)***	197.6 (220.8)	-820.3 (277.4)**	258.1 (296.8)	-1169.3 (871.5)	0.00424 (0.0334)	-1.101 (0.608)	-3.503 (1.196)**
2012	915.4 (113.4)***	1793.0 (293.1)***	2796.2 (346.1)***	733.3 (339.0)*	3014.1 (1059.1)**	-0.0432 (0.0330)	-4.333 (0.638)***	-7.136 (1.206)***
AGI>\$20k * 2012	1061.1 (137.8)***	-378.7 (352.3)	624.3 (412.4)	132.4 (396.0)	1030.0 (1261.1)	-0.00614 (0.0395)	1.390 (0.765)	3.186 (1.431)*
$R^2$	0.334	0.352	0.401	0.434	0.185	0.282	0.229	0.183
Mean	3858.6	4171.3	8370.9	2648.1	14352.5	0.353	22.46	34.32
Controls	X	X	X	X	X	X	X	X
State fixed effects	X	X	X	X	X	X	X	X
Obs	2370	2370	2370	2370	2370	2370	2370	2370

Heteroskedasticity robust standard errors are in parentheses. The sample is limited to students with parent income between \$10k-\$31k. The difference-in-differences estimates are in the third row. The first four columns report short run outcomes that are comparable to the first four columns of Table 3, while columns 5-8 report longer run outcomes. The mean of the outcome for students with income between \$20k-\$31k in 2012 is reported in the lower panel. Sample weights were used in all regressions.

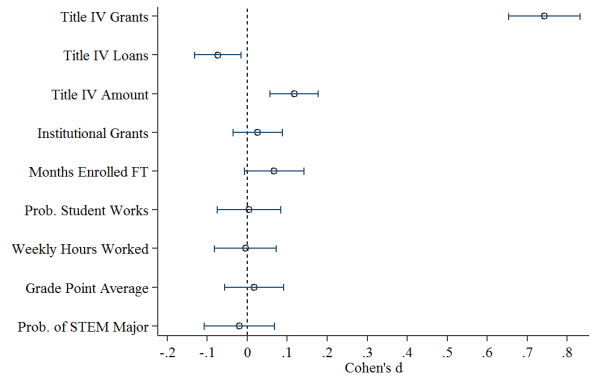
SOURCE: U.S. Department of Education, National Center for Education Statistics, Beginning Postsecondary Students. 2004 & 2012.

\*  $p < 0.05$ , \*\*  $p < 0.01$ , \*\*\*  $p < 0.001$



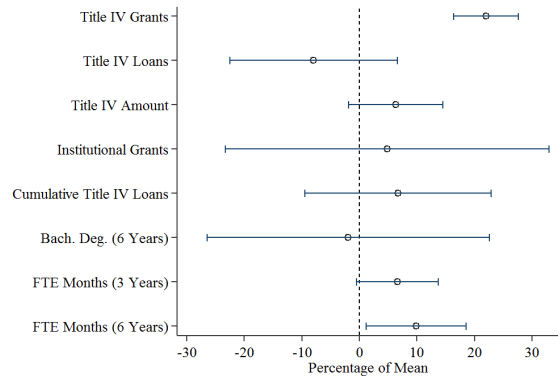
SOURCE: U.S. Department of Education, National Center for Education Statistics, National Postsecondary Student Aid Study, 2008 & 2012.

(a) Treatment effect scaled by mean (NPSAS)



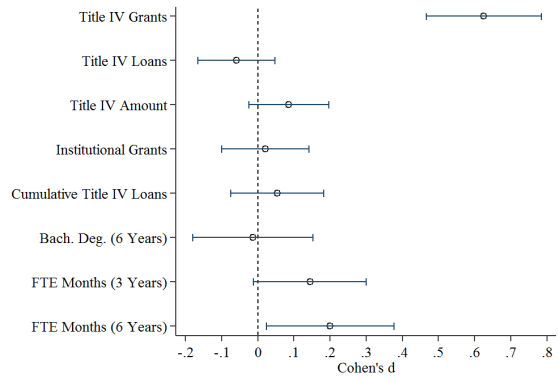
SOURCE: U.S. Department of Education, National Center for Education Statistics, National Postsecondary Student Aid Study, 2008 & 2012.

(b) Effect size (NPSAS)



SOURCE: U.S. Department of Education, National Center for Education Statistics, Beginning Postsecondary Students, 2004 & 2012.

(c) Treatment effect scaled by mean (BPS)



SOURCE: U.S. Department of Education, National Center for Education Statistics, Beginning Postsecondary Students, 2004 & 2012.

(d) Effect size (BPS)

Figure 3: Treatment effects across multiple outcomes

*Notes:* This figure presents difference-in-differences estimates of the effect of receiving an auto-zero-EFC on a variety of student outcomes. Figures 3a and 3b present short run outcomes from NPSAS whereas figures 3c and 3d present longer run outcomes from BPS. Circles represent point estimates while bars represent 95 percent confidence intervals. Figures 3a and 3c display the estimated treatment effect divided by the mean of the outcome for students between \$20k-\$31k income in 2012. Figures 3b and 3d display the estimated treatment effect divided by the standard deviation of the outcome for students between \$20k-\$31k income in 2012 (also known as Cohen's d).

to look at both enrollment effects and labor market outcomes. Because our data sample college freshmen and follow them for only six years, we are restricted to look at financial and academic outcomes within a six year window of first enrollment.

With all of that said, our findings match those of Denning et al. (2019) in several ways. We both find that receiving an auto-zero-EFC 1) raises grant aid in the short run, 2) lowers borrowing somewhat in the short run, 3) has no effect on GPA, 4) has no effect on short run work or earnings, and 5) has a small, marginally significant effect on short run enrollment intensity.<sup>7</sup> Moreover, we both find statistically significant, albeit modest, effects on long run enrollment intensity. But our findings differ on longer run graduation rates. Denning et al. (2019) find that auto-zero-EFC eligibility raised six-year graduation rates by 3.3 percentage points. Although our estimates are less precise, we find no significant effect with a slightly negative point estimate. This is consistent with Eng and Matsudaira (2021) who also find smaller and less robust effects on completion.

## 7 Persistence of Federal Aid

One way to reconcile our findings with those of Denning et al. (2019) may lie in the state of Texas's TEXAS Grant, which awards students in Texas a state grant up to the statewide average of tuition and fees. Denning et al. (2019) find that receiving an auto-zero-EFC raises the probability of receiving a TEXAS Grant. Crucially, once a student receives a TEXAS Grant, she is eligible to continue receiving the grant for up to five years, which adds a great degree of predictability to her financial aid. In contrast, it turns out that federal financial aid is surprisingly volatile from year to year. To illustrate, Table 5 reports the 2013 EFC's of students who had income between \$20,000 and \$31,000 in 2012. These students all had auto-zero-EFC's in 2012, but, of the 82 percent who completed the FAFSA for the next year (2013), 42 percent of them had an EFC above \$0, one-quarter had an EFC above \$1,000, and nearly one in six had an EFC above \$2,000.<sup>8</sup> Given the uncertainty over future financial aid, it is not surprising that a one-time increase in aid has a much smaller effect on educational investments than a guaranteed flow of aid over several years. Thus, our results highlight the importance of a neglected dimension

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<sup>7</sup>Denning et al. (2019) measure enrollment intensity in terms of credits attempted while we measure it in terms of months enrolled full time.

<sup>8</sup>Increases in the EFC reduce Pell grants dollar for dollar.

of financial aid—the stability and predictability of aid over a student’s college career.

Table 5: Next Year’s EFC Among Auto-Zero EFC Recipients

Mean EFC in 2013	\$1,033
2013 EFC > 0	42.2%
2013 EFC > 1000	24.1%
2013 EFC > 2000	15.2%

This table calculates the 2013 Expected Family Contribution (EFC) for students with parent income between \$20k and \$31k in 2012. These students all had an automatic zero EFC in 2012. 18 percent of these students did not complete a FAFSA in 2013, so they are excluded from the table. Sample weights were used (WTA000).

SOURCE: U.S. Department of Education, National Center for Education Statistics, National Postsecondary Student Aid Study. 2012.

## 8 Conclusion

Increasing the auto-zero-EFC threshold from \$20,000 to \$31,000 significantly increased federal grants received by students in this income range. Nevertheless, we find no discernible effect of this increased aid on a variety of student outcomes, which is consistent with the findings of Eng and Matsudaira (2021) but contrasts with those of Denning et al. (2019). We argue that our findings can be reconciled by recognizing a unique characteristic of Denning et al. (2019)’s setting—receiving an automatic zero EFC in Texas increased the probability of receiving a TEXAS grant that guaranteed students a flow of aid over multiple years. Federal aid programs offer no such guarantee; rather, federal aid can be quite volatile from year to year, and this volatility may blunt the effect of aid on students’ educational investments. More generally, we should expect that prolonged investments in human capital will be more sensitive to permanent increases in financial aid than to transitory increases. This insight has relevance for the design of policies which are intended to increase access to higher education among low-income students.



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