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The impact of federal administrative burdens on college enrollment

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Abstract

Government programs impose eligibility requirements to balance the goals of improving welfare while minimizing waste. We study the impact of eligibility monitoring in the context of Federal Application for Federal Student Aid (FAFSA) submissions, where students may be subject to "verification" requirements that require them to confirm the accuracy of the data. Using a matching on observables design we do not find that students flagged for verification are less likely to enroll in college, which contrasts prior research. Verification reduces grant aid received but average changes are small, raising questions about the benefits of this administrative process.

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1 Introduction

Government programs often impose eligibility requirements to balance the goals of improving welfare while minimizing waste. Requiring applicants to show proof of eligibility follows logically if resources are limited and should be targeted towards populations that would benefit the most. Federal programs have long focused on creating positive returns by, in part, reducing program expenditures towards fraudulent expenses, and a long economic literature postulates that raising application costs can improve societal welfare (e.g., Nichols & Zeckhauser (1982)). Yet incorporating principles of behavioral economics often produces the opposite finding, in that application costs lower participation rates by reducing initial applications from populations that might benefit the most, or pushing eligible individuals out of programs through excessive recertification requirements (Finkelstein & Notowidigdo, 2019; Homonoff & Somerville, 2021).

This paper investigates the "Verification" process of federal financial aid applications to examine how an administrative requirement intended to reduce fraud may alter postsecondary enrollment. Monetary subsidies for postsecondary enrollment aim to eliminate short-term credit constraints or other behavioral barriers that reduce postsecondary participation rates, as the returns to investment in education are typically large (e.g., Angrist et al. (2022)). The Free Application for Federal Student Aid (FAFSA) is an essential step for students to receive federal aid for college enrollment, and the government requires families to provide detailed data on family structure, income, and assets, in order to determine the allocation of grants and loans. Although federal financial aid aims primarily to help economically disadvantaged students, the complex process can create an additional obstacle for those who most need the support, and interventions to assist families to complete the form increases postsecondary enrollment rates (Dynarski et al., 2013; Bettinger et al., 2009).

Families who complete the FAFSA may be required to take an additional and underappreciated step referred to as "Verification," where applicants must provide supplemental documents to verify the accuracy of their submission. The process by which applicants are selected for verification is not well understood, with a key description stating the federal government uses "data-based statistical analysis...to select for verification...FAFSA applicants with the highest statistical probability of error and the impact of such error on award amounts" (ED, 2009, p.106). Public statistics identify that approximately one-third of FAFSA applicants are selected each year, with a higher probability of selecting low-income or ethnic minority students, though verification rates have declined in recent years (AlQaisi et al., 2020).

Although verification is intended to help reduce fraud, whether through correcting flawed data or via the threat of monitoring functioning as a tool to encourage honest reporting, there is little prior research on how this functions in practice.[1] One prior effort found that 59% and 75% of students at public four-year and two-year colleges exhibited no major change in Expected Family Contribution (EFC) after verification, respectively, with even higher rates of unchanged applications among the lowest income students (Rhodes & Tuccillo, 2009, Fig. 6, 9). The same report found a 15% rate of improper payments composed of a 9% overpayment rate and a 6% underpayment rate, suggesting that this huge administrative burden led to a relatively minimal gain in terms of reduced improper expenditures (Rhodes & Tuccillo, 2009, Fig. 18).

This project examines the role of FAFSA verification on students in several ways. We rely on first-time FAFSA submissions for dependent students who reside in California, with our data containing multiple rows per student per year as their information is updated. First, we examine who was flagged for verification and how often their initial submitted values change in a given year. Second, we use a matching on observables strategy to estimate the impacts of being selected for verification on postsecondary immediate and long-run enrollment. (In our data we observe whether students are flagged for verification on their FAFSA but cannot observe the actual steps of their verification process. For simplicity purposes, throughout the paper we use "being verified" or similar language to refer to being flagged for verification, and use "verified students" to refer to those who have been flagged for verification regardless of whether they complete the process.) Previous studies relying on related "selection on observable" strategies suggest verification is associated with lower levels of immediate college enrollment but have not yet examined long-term enrollment or persistence, or had the quality of our data to account for potential unobservable differences in flagged students (Wiederspan, 2019; Holzman & Hanson, 2020; Lee et al., 2021).

Our primary finding suggests no causal relationship between being selected for verification and subsequent postsecondary enrollment. Our point estimates identify an overall insignificant 0.1 percentage point (pp) drop in immediate enrollment at in-state public colleges. While some suggestive evidence shows a potential reduction in 4-year college enrollment and increases in 2-year college enrollment, most estimates are small and statistically insignificant. California supports postsecondary enrollment through its generous state aid program, the Cal Grant, and being flagged for verification reduces state aid receipt by 5pp (12%), which may be what induces these small shifts out of more expensive four-year colleges into nominally less expensive two-year colleges. (We also estimate causal impacts using a regression discontinuity design based on a policy change in December 2018, and again find null effects; unfortunately these results are statistically noisy and we place these findings in an appendix for the interested reader).

Our null results on postsecondary enrollment differ from prior studies (Wiederspan, 2019; Holz-

[1] The Education Department (ED) estimated "improper payments" of approximately \$6 billion in 2018, or about 6% of total outlays, though verification is just one of a number of mechanisms by which this might occur. For example, other mechanisms included actions like incorrectly awarded amounts based on Expected Family Contribution (EFC), and incorrect processing of student data during normal operations, along with a number of others (ED, 2009).

man & Hanson, 2020; Lee et al., 2021), and we note a few potentially substantive differences. Principally, we believe our selection on observables approach improves on prior work. We rely almost wholly on FAFSA data, and we observe the student's initial FAFSA submission before any endogenous changes to the family-reported income that often results from the verification process. In contrast, prior studies typically cannot capture this information, and rely on income proxies such as student self-reports on the American College Test (ACT) questionnaire form or median income from census blocks.[2]

We think these alternative methods are unlikely to adequately capture the underlying relationship between key variables such as income and verification, and so may not have sufficiently removed the bias inherent in these approaches. Another potential difference between studies is variation in treatment effects that would arise across state contexts, as we examine students in California, rather than Iowa, Tennessee, and Texas. Discussed in Section 6.2.5 below, one explanation could be that California's lower tuition rates, strong state-level aid programs, and perhaps more generally supportive environment, could combine to help students better navigate the verification process or access alternate sources of funds if they do lose access to aid. We cannot reject this result, though note that qualitative research in California has discussed the challenges students face in the verification process (Graves, 2022). We are able to replicate one prior paper in Iowa that relied on similar FAFSA data, and find that when we use their preferred sample selection approach and methodology we also produce negative point estimates on enrollment.[3] Yet when we employ our preferred methods using their sampling approach, we again produce a null result that eliminates this theoretical negative impact. This implies that at least some of the difference between our null results and prior negative impacts is due to what we believe is an improved methodology, rather than merely contextual difference.

On the one hand, it bears noting that our results are not a definitive answer as to the causal impact of verification. Without understanding the currently unobserved verification process, matching on

[2]For example, Lee et al. (2021) use self-reported family income from the ACT questionnaire, which categorizes family income into 9 brackets (e.g., less than 24 thousand, 24 to 36 thousand, … more than 150 thousand). As demonstrated in Figure 1a, Adjusted Gross Income (AGI) has a non-linear relationship with the verification rate. Merely matching with income brackets could fail to construct a comparable control group due to the income brackets failing to fully capture the variation in the verification rate, in addition to the concern about the accuracy of self-reported income. Although speculative, when we focus on just the lowest income bracket of families earning 24 thousand dollars or less, we find a strong negative relationship between AGI and the verification rate but a negative relationship between AGI and the student enrollment rate. Thus, relying on just comparisons within this bracket, without adequately controlling for these linear relationships in verification and enrollment, could lead to a spurious relationship indicating that those who are more likely to be verified are those less likely to enroll in college. Another concern is "regression toward the mean" if lower-income families are more likely to self-report higher income but are subject to higher verification rates, which could also introduce negative bias into the impact of verification on enrollment.

[3]The other two papers apply matching strategies that use data from outside the FAFSA, such as standardized test scores, that would not allow us to replicate their approach and do not reflect how the federal government would select for verification.

observable strategies may simply be unable to measure the true causal impact, and results could be sensitive to the inclusion of different variables or via different matching approaches. Yet we believe our results produce valid estimates for a few reasons. First, we show that our matching approach tends to minimize differences in background characteristics that we know are not explicitly used in the verification selection process, such as high school GPA. Although this is only suggestive evidence, the fact that these secondary characteristics do not differ between groups suggests that our matching strategy is accounting for a large proportion of differences between students selected for verification and those that were not. Second, even including these extra variables, which are highly predictive of postsecondary enrollment, does not change any of our main results. Given prior work on bounding treatment impacts based on unobservables in matching designs, these findings suggest that the true effects of verification on enrollment are likely to be small.

Although we find no explicit harm from verification on enrollment, the process itself requires significant expenditures in time and energy and produces only small changes in who receives aid and how much aid they are offered. Given upcoming changes to the FAFSA form, revisiting the methodology to create a more transparent process with lower levels of burden on the average student seems warranted.

2 Background

Students must complete the FAFSA to qualify for federal grants or loan aid. The FAFSA has long been critiqued due to its length and complexity, which creates a significant barrier to financial aid receipt for eligible low-income students (Dynarski & Scott-Clayton, 2013). Yet prior work on FAFSA's complexity has rarely delved into the issue of FAFSA verification, where applicants who have completed the FAFSA are asked to provide supplemental documents to verify the accuracy of their submission. A substantial literature has investigated how administrative burdens in social welfare programs can impede the take-up rate and reduce welfare for potential recipients of these benefits (Barnes & Petry, 2021; Homonoff & Somerville, 2021; Foote et al., 2019). Prior studies consistently show that reducing administrative burdens leads to higher program participation rates (Finkelstein & Notowidigdo, 2019; Drake et al., 2021; Herd et al., 2013; Foote et al., 2019).

Both the ED and colleges may select students for verification. ED applies "data-based statistical analysis" to detect the applicants with the highest likelihood of error on their FAFSA information and with the such error may affect the financial aid amount. However, the exact statistical model or method adopted by the ED is unknown. The ED also reports that in some cases, they will randomly select students for verification. Each college may also select for verification based entirely on their own discretion and criteria.[4]

[4]The information of this and the following paragraphs regarding the verification process are based on the FAFSA

After a student submits the FAFSA they receive a Student Aid Report (SAR) within 3–5 days (if they sign the FAFSA form with FSA ID) or two weeks (if they do not sign with FSA ID) either via email or mail. The SAR will report whether the student has been selected for verification by the ED, which is how we identify students in our data.[5] Colleges will notify the student directly if they have selected them for verification. When ED selects students for verification, they will also identify the "verification tracking group," in which each group requires different verification documents. The documents may include students' (and, for dependents, their parents') tax returns or wage statements, high school diplomas, a list of family members' names and relationships, and/or a statement of educational purpose. Regardless of which entity requests verification, the college is responsible for adjudicating the verification process. In some cases, colleges have the discretion to judge which type of documents are acceptable. For example, colleges usually require only a signed statement to indicate the student received SNAP benefits, but if a college doubts the validity of the information they might require the students to provide official proof from the appropriate agency.

When students are selected for verification, they need to prepare the documents based on the college's requirements. They are also asked to update information in the FAFSA system if they have been aware of any errors. After receiving student documents, colleges should compare the documents with the information on the FAFSA system and make adjustments as needed. Students cannot receive federal subsidized financial aid before completing the verification process. The deadline of the verification process depends on the type of aid. For the Pell Grant, the requirement is within 120 days after the last days of a student's enrollment.[6] For the Cal Grant, students need to complete the verification process within one year.

The FAFSA verification process might create administrative burdens in multiple respects. Moynihan et al. (2015) categorizes administrative burdens into three types: learning, psychological, and compliance costs. First, the verification process can be even more complex than FAFSA itself, enforcing huge learning costs on students subject to verification. Students need to submit their verification documents to *each* institutions they apply to and each institution might have different rules and requirements (Cochrane, 2010; Crutchfield et al., 2016; Cochrane et al., 2007; Warick, 2018). Students selected for verification are usually confused by the process and encounter difficulties in identifying the correct documents or materials needed, and may fail to complete the process because they do not become aware that their documents are incomplete (Cochrane, 2010; Graves, 2022; Vengas, 2006). Secondly, psychological costs can amplify the process by producing frustration due to the endless paperwork and miscommunication from their financial aid office (Cochrane,

application guide for students and colleges. More information is available at `https://studentaid.gov/apply-for-aid/fafsa` and `https://fsapartners.ed.gov`.

[5]Even if a student receives relatively early notice that they are selected for verification, they might still need to wait for the college's notification to know what documents they need to prepare, as discussed below.

[6]Or on another date specified by ED, usually in mid-September after the academic year, whichever is earlier.

2010; Crutchfield et al., 2016; Graves, 2019, 2022). Finally, the compliance cost of FAFSA verification is large, especially for low-income students. Students are often required to provide proof of their income, which may be especially hard for dependent students whose parents did not file tax returns, or requires students to get other assistance or signatures from their parents (Graves, 2022; Warick et al., 2017). Previous studies find that for the 2017–2018 application cycle, around 28% of people who were selected for verification did not complete the verification process (AlQaisi et al., 2020), and in one study of California community college students, the non-compliance rate was 30% (Cochrane, 2010).

Overall, previous studies have shown that FAFSA verification has created a vast and disproportionate burden on students from low-income families (Cochrane et al., 2007; Warick et al., 2017; Evans et al., 2017). Furthermore, evidence suggests that students who were selected for verification do not generally experience a major change in the total Pell Grant they receive, and less than 10% have lost their Pell eligibility (Crutchfield et al., 2016; Warick, 2018; AlQaisi et al., 2020; Evans et al., 2017). A study on higher education institutions also finds that the verification process is time-consuming and costly to colleges and their staff (Guzman-Alvarez & Page, 2021). The estimated national institutional cost estimated by Guzman-Alvarez and Page is $500 million, while the estimated "saved" taxpayer money from correcting FAFSA information via verification is around $428 million as estimated by AlQaisi et al. (2020).

Previous studies examining the impact of verification mostly rely on a "selection on observables" approach. We briefly summarize prior results here, but engage in an extended discussion later in the paper comparing out approach to theirs. They find that subjecting a student to verification is associated with lost federal aid (Cochrane, 2010; Warick, 2018; AlQaisi et al., 2020) and lower college enrollment rates (Wiederspan, 2019; Holzman & Hanson, 2020; Page et al., 2020; Lee et al., 2021). The change in federal aid is mostly due to failing to complete the verification process rather than verification leading to a large change in EFC (Cochrane, 2010; Warick, 2018; AlQaisi et al., 2020). The estimated enrollment gap between students subject to verification and their control groups ranges from 2 to 6pp across studies (Wiederspan, 2019; Holzman & Hanson, 2020; Page et al., 2020; Lee et al., 2021). These same studies also find that the negative impact is larger on enrollment in community colleges rather than four-year institutions (Wiederspan, 2019; Lee et al., 2021). Other qualitative studies find that even for people who have enrolled in college, getting verified still delays the disbursement of their financial aid, leading to additional difficulties and sometimes leading them to drop classes due to affordability (Crutchfield et al., 2016; Warick et al., 2017; Cochrane, 2010).

3 California Context

This project focuses on students in California who have submitted their FAFSA. In 2019, California enrolled almost 14% of all students in degree-granting postsecondary institutions, driven by the largest community college system (hereinafter referred to as CC) in the nation and the four-year California State University (CSU) and University of California (UC) systems (NCES, 2020). Approximately 63% of California's public high school students attend college, and of those that do, 85% enroll in these public colleges (57% and 28% in two- and four-year colleges, respectively) (Kurlaender et al., 2018).

Students in California submit the FAFSA for two purposes. The first is to access federal need-based aid (e.g., Pell Grants) and loans. The second motive is that California provides significant state aid through the Cal Grant program. To be eligible for the Cal Grant, applicants must submit the FAFSA and a one-page GPA verification form that is completed by high schools on the students' behalf. The single largest Cal Grant program, which is the one used by essentially all high school graduates, is the Entitlement grant, which requires students to submit their FAFSA by March 2. In short, students are eligible for the grant if they are low-income and have a GPA of 2.0 or above, or if they are middle-income and have a GPA of 3.0 or above. Exact income limits vary by year and family size, but in 2017-18 a dependent in a family of four was low-income if their family had an income of $50,100 or lower, and middle-income if above this amount but below $95,400.[7]

Students who are Cal Grant eligible can essentially select one of three payment options based on their sector of attendance. Students attending a CSU or UC can choose four years of full tuition and fee payments, which were approximately $5,500 and $12,500 annually, respectively, during this time period. Although the Cal Grant does not pay full tuition at private colleges, students can receive an annual subsidy of approximately $9,000 to attend a private college. Finally, the Cal Grant does not pay community college tuition but does offer an annual $1,672 cash "subsistence award" that essentially covers full-time community college enrollment, given that California has one of the lowest tuition rates in the country.[8]

4 Data and Sample

4.1 Data

This paper uses data on FAFSA submissions provided by the California Student Aid Commission (CSAC). In order to administer California's aid programs, CSAC has authorization to pull

[7] Income limits are available at `https://www.csac.ca.gov/post/cal-grant-income-and-asset-ceilings`.

[8] California also offers the California Promise Grant that covers community college tuition for certain groups of students, but we cannot observe Promise Grant receipt in our data.

FAFSA submissions from the U.S. Department of Education's Federal Student Aid (FSA) system, which is commonly referred to as an ISIR (Institutional Student Information Record).[9] The data we have access to are snapshots of ISIR records that CSAC archives at the end of each academic year, but each ISIR contains student SSNs that can be linked over time. Each individual can have more than one row ("transaction number") in the data, and the variable values can correspondingly change over time.[10] For example, in 2016-17, we find that 61% of individuals have two or more rows, with students flagged and unflagged for verification having more than one row 77% and 50% of the time.

Our data includes many of the fields typically included on the FAFSA form, though CSAC does not archive or does not make available all of the data elements. Basic self-reported background characteristics include items such as gender, citizen status, birth date, student and parental marital status, number of family members, educational goal, home zip code, and the colleges listed on the FAFSA form to which the student wants their financial information sent. There are also a number of measures of income and assets, including average gross income (AGI), net worth,[11] and EFC.[12] Cal Grant applicants also submit their high school GPA and a code that identifies their high school attended, which can be linked to high school details in the Common Core of Data (CCD).

We identify a student as flagged for verification if the "Verification Flag" variable is set to "Y."[13] FSA describes this flag as indicating "if a student has been selected for verification on any transaction." This field does not provide any additional details about their Verification status.[14] We focus on cases where the verification flag is set to yes in the first row of the student's ISIR records; once the verification flag is set to yes it remains this way for every subsequent transaction in that year. (Most but not all students who are selected for verification have the flag set to yes in their first transaction, and later we test the robustness of our results by including these students in both the treatment and comparison groups). We use the verification status in students' first transactions as the treatment variable. In our sample, around 11% of applicants did not get a verification flag

[9]This analysis only uses ISIRs from students with a California residence.

[10]FSA documents list a transaction as "an interaction between the Central Processing System (CPS) and a financial aid applicant or a school that changes any of the data on a student's record."

[11]Net worth is defined as the sum of cash, savings and checking, net worth of investments, net worth of business and investment farm, and adjusted net worth of business and farm.

[12]EFC determines students' federal student aid eligibility and award amount. For general dependent students, the EFC is defined as the sum of available income and contribution from assets (discretionary net worth times 12% of the asset conversion rate) divided by the number of family members in college. Students who have AGI below a given cut-off ($25,000 in 2016-2017) could get an automatic zero ("autozero") EFC. The details of the calculation of EFC are available at the ED website: `https://studentaid.gov/sites/default/files/2017-18-efc-formula.pdf`

[13]Both the federal government and colleges can select students for verification, but the verification flag we use only includes those selected by the federal government.

[14]One useful variable that is unfortunately omitted in CSAC's archives is the Verification Tracking Flag, which identifies the student's verification group (Standard, Custom, Aggregate, or Household Resources), and would normally provide some details as to which fields the student is required to confirm.

in their first transaction but eventually received verification in later transactions. We use the initial verification status instead of the final verification status because the change in verification status might be an outcome of student enrollment.

In our data, we only observe whether students are flagged for verification, but we do not know whether they have gone through the verification process or validated their FAFSA files. For simplicity purposes, throughout the paper, we use "being verified" or similar language to refer to being flagged for verification and use "verified students" to refer to those who have been flagged for verification regardless of whether they complete the process.

When assessing the impacts of verification on postsecondary outcomes, we use two primary measures: (1) in-state public college enrollment and (2) state aid receipt. The enrollment measure comes from individual-level files shared with CSAC by the CC, CSU, and UC systems, and are dummy variables that indicate early semester term-level enrollment (i.e., Fall and Spring, or Winter for colleges using the quarter system).[15] Throughout the analyses we combine the enrollment/aid information at UC and CSU into one group labelled as "four-year colleges"; separating these into two separate variables does not change any results. We supplement these enrollment measures with CSAC data on the Cal Grant, the state aid program.[16] Our data are individual-level records that identify for each student the term that they received payment, in which sector they were enrolled, and the monetary value of the award.

We use both data sources to identify postsecondary enrollment, as each measure provides slightly different information. One drawback to the enrollment data is that they cannot fully capture persistence in the CSU and UC systems, as enrollment records are only available if students continue to submit the FAFSA in subsequent years. Nonetheless, if a student is unobserved this indicates that they did not resubmit their FAFSA, which either indicates dropout or that—in even the best-case scenario—a student is foregoing financial benefits. The benefits of using the Cal Grant data are threefold. First, they provide a validity check on the enrollment data provided by the state. Second, they capture some additional private college enrollment, estimated to be approximately 4% of high schoolers' college attendance (Kurlaender et al., 2018). Third, they tell us whether verification alters students' state aid receipt, either through changes to family income or by invalidating the FAFSA data if students do not complete the verification process. The state aid data have some limitations: (1) they are reliable mostly for students who submit by March 2 and meet the income and GPA eligibility criteria, though this constitutes the large majority of high

[15] Each public college is required to share enrollment records with CSAC by October of the Fall term, so there may be some unobserved variation across colleges in the exact date when these values were provided. State law requires CSU and UC enrollment records to only include students whose FAFSA listed income below $150,000 but in practice, this covers 96% of all FAFSA submissions and over 99.9% of observations who we observe as subject to verification.

[16] We focus on high school graduates, though for older students who are two or more years past high school there is an alternate program that allocates awards in a competitive fashion, but is significantly smaller and less consequential for our analysis.

school graduates who submit the FAFSA; (2) students who enroll less than half-time cannot receive state aid; (3) prior work, internal to CSAC, identifies many students who enroll in a community college but do not take the state aid for various reasons, such as desiring to save it for later transfer to a four-year college. Nonetheless, taken together, these two data sources capture a substantial portion of true postsecondary enrollment decisions. In about 2% of cases, we find that students were enrolled in two or more segments (CC, CSU, or UC) in the same year. This could occur if students first enrolled in one segment and then transferred to another, or if students were enrolled in a four-year college but elected to also take credits in a community college simultaneously. In this case we identify this student as enrolling in a 4-year over a 2-year college, though allowing for simultaneous enrollment does not change results.

4.2 Sample

Our selection on observables approach uses data on FAFSA applicants from the 2016 and 2017 academic year cycles. The 2016 cycle includes students who began submitting from January 1, 2016, for 2016-17 enrollment, whereas the 2017 cycle includes those who began submitting from October 1, 2016, due to the initiation of the "prior prior year" (PPY) FAFSA process that began at that time Bettinger et al. (2022).[17]

We start with FAFSA records on all California residents but then restrict this main sample along the following dimensions. We first identify students who are first-time freshmen and first-time filers (i.e., we can identify if they filed the FAFSA in prior years, even though we lack any of their earlier detailed data). We focus on first-time filers as we want to identify impacts of verification among students experiencing it the first time, as those who have previously experienced verification may have exited the system or adapted their submissions in response to prior experience, making an estimation of impacts challenging. We are also particularly interested in first-time freshmen as we want to identify the impact of verification on initial college attendance. We then restrict to dependent students, for two reasons: (1) first-time filers and first-time freshmen are largely dependents, and (2) the unobserved verification algorithm may differ between dependent and independent students, and this eliminates this potential confounding. The sample size at this intermediate step is 460,372 for the matching sample. We further extend our analysis to independents and returning filers in robustness checks.

For this intermediate sample, Figure 1 shows the sample size and average verification rates (as measured by the ISIR Verification flag in the first transaction) by AGI, EFC, application date, and—for students who list high school—the proportion of free or reduced price-lunch (FRPL) status in

[17] We primarily focus on these years so that we can track student persistence over a longer time frame. In other analyses not presented here, we find that predictors of verification change from year to year, and verification rates may have decreased due to internal policy changes, making year-to-year comparisons challenging (AlQaisi et al., 2020).

their high schools. Figure 1a shows that students below the automatic zero EFC threshold (i.e., below $25,000 in income in those specific years) have relatively lower verification rates compared to middle-income students, who bear the highest verification burden. High-income students are least likely to be verified, in large part because so few are Pell Grant eligible. Figure 1b illustrates that students with EFC above the Pell-Grant eligibility cutoff have an extremely low likelihood of being verified. As revealed in Figure 1c, students who submit after the academic year begins have higher verification rates; although a large portion of students submits by the March 2 state aid deadline, there are still a substantial number of students who do not file until they are enrolled in the Fall or considering Spring enrollment. The last figure is simply illustrative and shows that students who attend high schools with higher poverty rates are subject to higher verification rates. Although this is driven by the correlation between family income and high school characteristics, it reinforces how these burdens fall on groups with higher needs, who are more likely to attend college without completing their degree.

As a result of the analysis in Figure 1, we make two additional restrictions. First, we restrict to students who are Pell Grant eligible. Figure 1b shows that students who are not Pell-eligible, as measured by the maximum EFC threshold, are rarely verified in our sample. Finally, we also exclude applicants who submit the FAFSA after August 1, in order to remove students who submit after the term begins. Here we are concerned about reverse causality, where students might experience verification as a result of enrollment, whereas we want to estimate how verification impacts later enrollment. The final sample size is 236,245 unique individuals.

The first two columns of Table 1 report the summary statistics of our first-time, dependent, Pell-eligible who submitted prior to August of their application cycle; we revisit the subsequent columns in the Results section below. The first three columns report the statistics of the original sample by comparing those who are verified (the "treatment" group) to those who are not (the "control" group), prior to any matching strategies. Verified students are, on average, from larger families with higher income, at least among the Pell-eligible sample, and were less likely to have reported filing a tax return as of the FAFSA submission date.[18] Besides the information listed on the FAFSA form, verification status is also correlated with students' high school GPA and various high school characteristics.

5 Empirical Strategy

In order to identify the impact of getting verification, we adopt a matching approach to construct a counterfactual that balances on selected variables with the people who get verification.

[18] In the full population we find that high-income students are rarely verified, but among the Pell-eligible sample, those with higher incomes are more likely to be subject to verification.

Given that the exact formula used to determine verification is unknown, we use FAFSA data and matching on observables strategy in order to eliminate, as much as possible, potential confounders that are correlated with both verification and the student's background characteristics. When the ED selects applicants for verification, it is reasonable to assume that they rely in large part on the observable variables that are included in a student's FAFSA submission. Nonetheless, there remain two additional concerns to assuming our matched comparison results produce a causal estimate of verification's impacts. The first is common to all matching strategies, in that our estimates rely on using the correct functional form for that matching process. Given we have limited information on how the ED sets up the algorithm for verification selection, and can observe non-linearities in some predictors of verification, our main approach is to see whether our results vary across a variety of different matching methods.

The second concern is that ED links students to other federal data sources, potentially including the Internal Revenue Service (IRS), Veterans Affairs, Department of Homeland Security, and others, and there may be flags raised by these matches that are the triggers for verification status. One example worth noting is that students can select to use the IRS Data Retrieval Tool (DRT) to import their tax return information directly from the IRS, and students who do not use IRS DRT are more likely to be flagged for verification (Cheng, 2017; Narayan, 2020). We do not have the variable indicating whether the applicants used the DRT. To help address this concern, we include the variable which identifies the applicant's tax filing status (a self-report on whether they had already submitted their taxes), along with other variables such as the week of submission, which correlates with the likelihood of having filed a tax return.[19]

When considering which variables to include in the matching process, this paper first utilizes a machine learning approach to detect which variables matter the most to predict the verification status. Specifically, we conduct regression tree models multiples time with random sets of samples and calculate the chance of each variable being selected.[20] For every single model, we include almost all variables in our dataset, including the FAFSA variables and Cal Grant application variables.[21] Figure A1 in Appendix A demonstrates the summary results from the regression trees

[19]See `https://studentaid.gov/help/irs-drt-eligibility` for the eligibility of using IRS DRT.

[20]The basic idea of the regression tree is to first separate the samples into two sets (branches) according to one selected variable (such as $X_1 > 5$ and $X_1 \leq 5$) in order to make the observations within one branch are most homogenous and are most heterogeneous from another branch. And then repeat this procedure multiples time in order to "grow" a tree (De'ath & Fabricius, 2000). The advantage of the regression tree is that it considers the nonlinear relationship and multi-interactions. This study utilizes the package $crtrees$ in Stata 16 to perform the analysis.

[21]Specifically, we include citizen status, birth date, high school diploma status, gender, parental education, parental marital status, tax filing status, number of family members, number of members in college, auto-zero EFC, simplified test, AGI, untaxed income, additional financial information, IRA payment, IRA distribution, untaxed pension, interest income, total income number, income tax paid, total allowance, available income, adjusted available income, net worth, asset protection allowance, discretionary net worth, total contribution, EFC, date of application, high school GPA, high school title I status, high school proportion of FRPL, high school racial and gender composition.

model. We found that AGI, EFC, total income number, date of submission, and other FAFSA variables composing the calculation of EFC dominated the prediction model. In contrast, some student demographic variables (e.g., gender, age) and high school characteristics are rarely being selected. In our following analysis, we only include the top 10 variables identified by the regression tree models in our matching process.[22] However, we conduct another robustness check in Appendix B which includes all variables in the matching process, and the main conclusion remains the same.

After selecting these variables, we employ the Entropy Balancing (EB) approach to estimate the impact of verification. The EB method matches on multiple moments (e.g., variance, skewness) rather than just on average values, which helps handle non-linearities in the relationship between verification and background characteristics (Hainmueller, 2012; Hainmueller & Xu, 2013). Previous studies find that EB performs better than many other traditional matching approaches (such as propensity score matching [PSM], propensity score weighting [PSW], or Mahalanobis distance matching [MD]) (Iacus et al., 2008, 2012; Watson & Elliot, 2016; Zhao & Percival, 2017; Phillippo et al., 2020). We discuss the matching process in more detail in Appendix A.

One concern in all matching models is whether the variable selection adequately accounts for selection into treatment. Described below, we show strong imbalance between verified and unverified students on variables not included on the FAFSA, such as high school GPA, and that these observable differences are dramatically reduced after our EB matching process even though we do not explicitly take these variables into account. Although not a guarantee that our matching process completely solves the selection issue, this result provides some evidence that our approach is not obviously flawed and reduces concerns about potential sources of bias. We also show that the inclusion of these ancillary variables after the EB process — many of which are independently strong predictors on enrollment and persistence — does not change our results, thus providing additional evidence that unobservable differences are unlikely to be driving these results.

6 Empirical Results

6.1 Balance Tests

Table 1 reports the summary statistics of our first-time, dependent, Pell-eligible, and submitting before August sample, with the first section describing those who were selected for verification (column 1) and not selected (column 2), along with the magnitude of the difference between the two groups (column 3). The second section of this table shows results for the EB approach, with the new control group (column 4). After using this EB approach, there are no longer any statisti-

[22] These variables have more than 20% of the chance of being selected. The 11th variable only has around a 10% chance of being selected.

cally significant differences (column 5) between verified and non-verified students on the selected FAFSA variables (e.g., tax filing status, income, EFC).

In the bottom half of Table 1 we examine the distribution of two additional characteristics that we potentially observe due to the Cal Grant state aid application, that are not provided as part of the FAFSA or the verification process: high school GPA and high school attended.[23] We note in the first set of columns that whether a student provides a GPA, the value of the GPA, and many values associated with their high school (e.g., ethnic distribution of students, percent of FRPL students), are all significantly different between verified and unverified students at the $p < 0.01$ level.

In the final panel of Table 1, we compare the application portfolio of the treatment and control groups. The variables show whether students listed any CCs, CSUs, UCs, and other colleges on their FAFSA forms. The application portfolio serves as a proxy for students' self-aspiration for college enrollment. The results suggest a moderate level of differences between the two groups.

Columns (4) and (5) of Table 1 shows that after engaging in the EB processes, there is an improvement in balance in the high school GPA, high school values, and application portfolio. For instance, prior to the matching process, the verification group, on average, holds a GPA of 0.07 points higher than the non-verification group, but the differences shrink to less than 0.02 points after matching. Similar patterns show in the high school characteristics. For example, the verification group was 3pp less likely to be eligible for FRPL than the non-verification group, but the gap reduces to 0.6pp after the EB process. The differences in application portfolios are also being minimized, with all differences less than 1pp. Though some values remain statistically different, this is driven largely by our large samples rather than due to excessively large disparities in background values. Thus the EB approach minimizes differences—even among variables which were not taken explicitly into account for matching purposes and could not be observed by the federal government—as most of the differences in high school characteristics become statistically insignificant.

We present results from the EB approach below but show alternate matching results in Appendix B. In addition, appendices also present results that include all FAFSA variables (the second panel in Table 1) and add the GPA, high school values, and application portfolios to the matching approach. In general, alternate approaches produce results that are similar in direction though occasionally fluctuating in magnitude. This is likely the case due to the relatively small differences across treatment and control groups in these alternate values.

[23] Although the FAFSA does have a field for high school name and city/state, this is a text field that is often incomplete and contains spelling errors and seems unlikely to be used for verification purposes. In contrast, the high school value for the state aid submission is a numeric value that identifies the high school and is completed by the high school's counselor or other staff

6.2 Impacts of Verification

6.2.1 ISIR transactions and changes to submitted data

Table 2 shows the relationship between verification and three sets of outcomes: (1) changes in FAFSA content in the current year; (2) public college enrollment, and (3) state aid payments. Panel A shows raw differences between verified and unverified students. These results are simply to show how large differences are before correcting for observable confounders between verification and enrollment but are not discussed in the text. Panel B shows results from the EB approach.

We first note that, as expected, being selected for verification leads to a roughly 22pp increase in the likelihood of having updated the ISIR file at least once, over a baseline rate of 54%.[24] This is as verification often requires students to update their information, which creates a new transaction record in the ISIR file. Of course, some students subject to verification will not update their information and remain with one row, which may lead them to forgo financial aid.

A key question is which FAFSA characteristics are likely to change between transactions and how the change affects financial eligibility. In Table B1 in Appendix B, we focus on students who have multiple transactions and compare changes in key values between their first and the last transactions. One limitation is that we have no information on whether applicants who had not updated their FAFSA records was because they failed to complete the verification process or that their initial submission was ultimately accurate and did not require updating within the system. There were 18% applicants in the verification group who experienced no change in their FAFSA record. Still, the investigation of the change record for those who have updated their FAFSA is still informative.

We find few changes in demographics, such that gender, citizen status, age, and even dependency status remain unchanged for almost all students. Other variables change for likely natural reasons; for example, the number of students who have filed their tax return increases from 59% in the first transaction to 93% by the final transaction we observe, likely as time has passed for this to occur. However, we find significant changes across transactions when examining income and family structure. One-quarter of respondents change their household size — with an average drop of 0.3 people. AGI changes for 41% of students, with an average increase of $1,469. These changes to income and family composition lead to changes in EFC used to calculate Pell Grant aid, which increases by approximately $1,000. Simulated Pell Grant aid via changes in EFC declines by roughly $200.[25] The change in income and family size also affects the eligibility for Cal Grant.

[24] The baseline is the control group EB weighted average.

[25] We use the simulated aid amount here because we do not have exact data on the amount of aid received. The simulated amount is based on assuming that all students received the maximum award amount while attending full-time, thus providing an upper bound of the impact of verification on grant receipt.

The simulated maximum Cal Grant drops by $200 correspondingly.[26] Table B2 in Appendix B investigates a similar pattern but uses the EB approach to examine the impact of verification on aid amount. The result suggests that verification leads to a $235 drop in simulated Pell Grant and $168 drop in Cal Grant, though we note these are upper bound estimates that assume every student enrolls full-time.

Figure 2 provides more details about the distribution of changes, focusing just on EFC and simulated Pell Grant payments. For dependents flagged for verification, we see both gains and losses in EFC, such that some students may actually receive more funding as a result; this corresponds to a prior government report by Rhodes & Tuccillo (2009). Among verified students, 39% and 20% exhibit a gain or a decline in EFC, respectively, at least among students who have more than one row in the FAFSA transaction records. Yet as noted above, EFC increases by approximately $1,000, driven by a high proportion of students who experience very large gains. For comparison, the right set in Table B1 reports the changes in EFC for students who are not subject to verification but simply have multiple transactions in their ISIR records.[27] Only 9% of the control group observations have experienced a change in EFC compared to 59% of the ones in the verification group. The bottom half of Figure 2 shows changes to likely Pell Grant aid received via simulations of changes in reported EFC. More than 10% of verified students lose $2,000 or more of federal aid, compared to 3% who gain $2,000 or more. In contrast, nearly 90% of the applicants in the control group experienced no change in their simulated Pell Grant.

6.2.2 Impact on enrollment outcomes

We return to Panel B in Table 2. Focusing on the EB matching results shows no difference in postsecondary enrollment patterns, as verified students are a statistically insignificant 0.1pp less likely to be enrolled in a public college in the Fall semester. The 95% confidence interval is 0.9pp to —1.1pp, which rules out large negative impacts of 2 to 6pp as reported by prior studies. (Wiederspan, 2019; Holzman & Hanson, 2020; Lee et al., 2021). Panel A shows that in our data, the OLS estimate without any covariates is –0.005 ($p < 0.05$), suggesting a slightly downward bias of OLS.

Columns (5) to (8) report the impact on state grant receipt. We report impacts on the likelihood of receiving state aid, and report simulated changes in actual dollars received in Table B2 in Appendix B.[28] We do find that verification is associated with a large 5pp decline in Cal Grant

[26] The maximum amount is simulated with the assumption that the students attend the UC system full-time.
[27] The control group here is the same as our main sample, i.e., first-time, dependent, Pell-eligible people.
[28] We use dummies indicating whether a student received a state grant payment as this was the data provided for this project. We do not observe actual aid received. The Cal Grant tends to be a fixed amount of financial aid, in that students at four-year colleges all get full tuition and fees (which does not vary much within the CSU sector or the UC sectors) or the subsistence cash award at the community college. We assume all students enroll full-time in order to produce an upper bound estimate of the impacts of verification on total aid received.

receipt (over a baseline of 42%), evenly split between community colleges and four-year colleges (CSU, UC, and private non-profits). This is likely due to verification leading to increases in total income, as Table B1 shows that almost 3% of verified students who have multiple transactions are no longer eligible for Cal Grant B, which is the primary source of Cal Grant state aid for community college enrollment.[29] Another reason for a decline in state aid is if some students fail to complete the verification process, and so have no updated FAFSA record required for eligibility.

Comparing the impact among different segments (2-year vs. 4-year colleges), there is suggestive evidence that verification leads to a loss of state aid (1.9pp) and enrollment (0.8pp) among 4-year college students, leading to a slight but not statistically insignificant increase in community college enrollment of 0.7pp. Although there is a negative impact of 2.6pp on using state aid to attend community college, this is not a logical contradiction; many students who attend community college and are state aid eligible do not receive aid as they either: (a) choose not to use the program while waiting for later transfer; (b) enroll less than half-time, or; (c) show up as enrolled in the community college but drop out through the semester, which often results in them not receiving the state aid payment.

The immediate enrollment results shown in Table 2 are similar to long-term enrollment results observed in Table 3. Examining the first four years of potential enrollment, we find no evidence that students are more or less likely to enroll after being verified. The slight 0.8pp decline in four-year enrollment observed in year one shrinks over time, becoming a statistically insignificant 0.2pp decline by year four.

Switching to long-term measures of Cal Grant receipt provides two pieces of evidence that might explain these enrollment results. First, although there is a close to 3pp decline in state aid receipt at community colleges in the first year, this drops to a 0.4 to 0.5pp decline in the third and fourth years. This shift is due to the large dropout rate of community college students, with 46% of our sample enrolled in the first year declining to only 25% in the fourth year. Although 14% of the non-verified students used state aid at the community college in year one, this has declined to 2% in year four. Overall, exit rates from community colleges are high, and the additional verification burden does not appear to be a significant predictor of any long-run enrollment measures. Examining state aid receipt at 4-year institutions provides some more consistent evidence that the declines in 4-year institution enrollment may indeed be real, although small in magnitude. We find consistent evidence that state aid receipt declined by 1 to 1.9pp, and enrollment declines are roughly 0.2 to

[29] Although speculative, this loss of state aid could drive some students out of the four-year system, with enrollment results showing a small decline in CSU and UC enrollment matched by a small increase (1 pp) in community college enrollment. This matches internal CSAC research, which finds that essentially all CSU and UC enrollees who are Cal Grant eligible use the state aid, whereas many community college students who are Cal Grant eligible do not. This is because community college students may choose to hold onto aid, hoping to later transfer to a four-year college, enroll less than half-time, or quickly drop out before the aid payments are transferred.

1pp.[30]

6.2.3 Robustness Tests

Table B3 in Appendix B examines the impact based on alternative regression or matching approaches. Panel A reports the results from OLS with covariates.[31] Panel B is based on the EB approach as in our main results but further includes covariates. Panel C includes all variables in the EB matching process. This final setting accounts for key characteristics that are likely unobserved by the ED, including high school characteristics, GPA, and institutions listed on the FAFSA form. Although there are differences in magnitude, all the results point to similar patterns as described above. In all the settings, there are negative impacts of enrolling in 4-year colleges and positive impacts of enrolling in 2-year colleges, though some estimates are not statistically significant. Consistent evidence shows the pronounced negative impact on Cal Grant receipt.[32]

6.2.4 Subgroup Analyses and Additional Results

We conducted a number of subgroup analyses and additional results to examine potential differences across groups in verification's impacts. Panels A and B in Table B4 in Appendix B examine the impact of verification by FAFSA submission time. We separate applicants into those who submit before and after the March 2 state aid deadline. The results suggest that the negative impact on Cal Grant receipt is—as fully expected—driven by earlier submitting students who met the deadline requirements.

We also extend our results to different samples of students. In short, most groups we examined show no changes to postsecondary enrollment as a result of verification. Panel C in Table B4 shows results for independent students, still restricting to first-time, Pell-eligible individuals. While the result shows a 2.1pp drop in public 2-year college enrollment, the estimate is quite noisy and

[30] Two potential explanations could explain the long-run impact of verification on aid receipt. First, the result could be driven by students' aid application decisions. Using the same matching model, we find that verification in a given year leads to a 3pp drop in the likelihood of students submitting their FAFSA in the next year (which also makes them lose their eligibility for state financial aid). The second potential mechanism is that the federal government is more likely to flag students previously selected for verification, making students more likely to experience the same burden in the next year. Using the same matching model, we find that verification in a given year leads to a 4pp increase in the probability of being flagged for verification in the next year, conditional on submitting FAFSA.

[31] The covariates include gender, citizenship status, birthdate, parental marital status, parental education level, tax filing status, number of family members, number of family members in colleges, AGI, total income number, total allowance, income tax paid, EFC, dummies indicating zero EFC, auto-zero EFC status, simplified need formula status, available income, adjusted available income, untaxable income, untaxable pension, IRA payment, interest income, net worth, APA amount, DNW amount, total contribution, number of days of submission from application open, submit FAFSA on the weekend, dummies indicating the week of FAFSA submission, high school GPA, high school fixed effect, and colleges listed on FAFSA.

[32] We also adopt but do not present an alternative matching process of Coarsened Exact Matching (CEM), which further accounts for the potential interactions between matching variables. These results yielded the same conclusion.

nonsignificant, and there are no large changes to state aid receipt, largely because few of these students are eligible. The lack of significant changes may also be explained in part by the fact that this group experiences few changes across their FAFSA records after verification.[33] Panel D and E in Table B4 examine whether there are differential effects for returning students. We find no impacts on overall enrollment, though some evidence that verification can shift students out of four-year colleges and into two-year colleges. Panel D shows that students who were not subject to verification last year only experienced a total 1.3pp drop in state aid receipt. Panel E examines returning filers who were verified in the prior cycle. Perhaps given their experience with verification, the enrollment impacts are null, and we see smaller and statistically insignificant negative impacts on state aid receipt of 0.6pp.

A reasonable argument for the null impact on enrollment could be that verification both increases and decreases financial aid, thus canceling itself out. Table B5 performs a subgroup analysis based on initial EFC to explore this possibility. Students with an initial EFC just above the Pell eligibility threshold (therefore, not eligible for the grant) could only experience an increase in their aid from verification. In contrast, applicants with an initial EFC of 0, which provides the maximum Pell Grant, could only experience a decrease in their aid amount from verification. Panel A of Table B5 shows that while people with initial EFC greater than Pell cutoff experience an increase in the eligibility and simulated aid amount, this does not increase their enrollment. On the other side, Panels B and C demonstrate that while people with lower initial EFC experienced an average 1pp to 5pp ($212 to $224) decrease in Pell eligibility (via our simulated aid amount), they also do not exhibit any significant drop in enrollment.

Our primary findings reveal a slight shift from four-year colleges to two-year colleges. To further investigate this trend, we conducted a subgroup analysis considering students' application portfolios.[34] The outcomes of this analysis are documented in Table B6 in Appendix B. The results indicate that students who are considering both four-year and two-year colleges — which we identify by the colleges the student lists on their FAFSA form — exhibit the largest point estimate in terms of transitioning from four-year to two-year institutions. This group experiences a 2.7pp ($p < 0.05$) decrease in four-year enrollment coupled with a statistically insignificant 1.7pp increase in two-year enrollment. Although we cannot identify at which institutions students worked on the

[33] We compare changes in FAFSA variables across transactions for independents. Although independent students also experience an increase in income and EFC and loss of federal and state aid eligibility, those changes are similar to control group independents who have multiple transactions, but are not verified.

[34] The application portfolio is established from the list of colleges that students include on their FAFSA form, as we lack information regarding the specific colleges to which students ultimately submit their applications. Students are supposed to list at least one college and have the option to list up to ten colleges on their FAFSA form, with the flexibility to revise this list as needed, though in our data we found that 8% of students did not have any information on FAFSA listings. When a college is listed on the FAFSA form, the family's financial information is transferred to that institution and may be used in making decisions regarding institutional financial aid.

verification process, it seems that students on the margins of four-year and two-year enrollment may lose access to aid that shifts them out of more expensive four-year colleges into their alternative choices; this may be stronger in the California context where community college tuition rates remain among the lowest nationwide. Students who only list four-year colleges are unlikely to make this transition, with an insignificant 0.4pp decrease in four-year enrollment and a 1.2pp ($p < 0.1$) increase in two-year enrollment. Individuals who exclusively list two-year colleges on the FAFSA form demonstrate no discernible change in four-year enrollment and an insignificant negative 0.8pp decline in two-year enrollment.

6.2.5 Comparing Estimates to Prior Verification Papers

Our estimated null effect is robust to various specifications and samples, but there remains ambiguity as to whether our results differ from previous studies due to improvements in the methodological approach, from differences in the state context, or some other factor. We use data from California, a low tuition state with a large public college system, whereas prior papers were situated in Iowa, Tennessee, and Texas (Wiederspan, 2019; Holzman & Hanson, 2020; Lee et al., 2021). One approach to addressing this issue is applying the same sample selection process and methodology as prior papers to our California data, and examining how this changes results. We can only do this with the Wiederspan (2019) paper in Iowa, as the other two papers choose to use non-FAFSA data as key matching variables, thus preventing replication. For example, these papers use SAT and ACT standardized test scores as a covariate for matching, which is both unlikely to be part of the verification matching process and is not observed in our data. In addition, prior studies sometimes use income variables from proxy sources, rather than the FAFSA reported family income that likely drives the actual verification process. For example Lee et al. use income from the ACT questionnaire and Holzman & Hanson use income from American Community Survey linked at the census block level. Finally, each paper makes different functional form assumptions that may drive differences. Even assuming that the data proxies are accurate reflections of underlying income, Figure 1a shows a non-linear relationship between AGI and verification rate that may not be captured via linear functional forms (Holzman & Hanson) or income brackets (Lee et al.), and so may fail to construct an appropriate control group.

Table B7 shows the replication results which apply Wiederspan (2019)'s model to our data. Adopting the same approach as Wiederspan, the sample in this case is first-time filers who are undergraduates, above 18, and Pell-eligible.[35] Panel A reports the OLS result without covariates,

[35] We further exclude applicants who submit the FAFSA after August 1, due to the reverse causality concern as discussed in section 4.2, though Wiederspan did not exclude these people. In addition, we find that when including the applicants after August 1, the OLS results with or without covariates may produce coefficients with even larger negative bias.

using the Wiederspan approach on our California sample. Being subject to verification is associated with a 4pp drop in the overall in-state public college enrollment rate (see Column (6)). We then include the same set of covariates as Wiederspan's paper in the model, but now applied to the California data.[36] The result suggests that verification leads to a 2.7pp drop in in-state public college enrollment (see Panel B, Column (6)). This point estimate is close to the 2.3pp decline revealed by Wiederspan. Panel C then applies our EB approach to the same Wiederspan sample, to see whether our new methodology continues to produce a negative point estimate or, as we find, shows no causal impact of verification on enrollment. The negative impact on enrollment disappears when using the EB approach (see Panel C, Column (6)), and actually results in a positive but marginally significant 1.5pp treatment effect (only significant at the 10% level).

These results show that the difference between our main findings and prior papers, at least for Wiederspan, is likely not due entirely to contextual differences but is driven by the estimation strategy. Using our California sample but adopting Wiederspan's approach produce results similar to what he found in Iowa, but improving the matching process eliminates these negative enrollment results that have been associated with the verification process. Although we cannot do this for all prior papers, this provides at least some suggestive evidence that context alone cannot explain the difference in results.

7 Discussion and Conclusion

This paper uses California FAFSA data and applies a matching approach to examine the impact of FAFSA verification on enrollment and state aid receipt. Yet, suggestive evidence shows a small shift out of four-year colleges and into two-year colleges, perhaps driven by the loss of state aid. Our main sample is first-time, dependent, Pell-eligible students, who are the students likely least familiar with the financial aid application and verification process. We suspect these students are likely more susceptible to verification's adverse impacts, and when we extend our analysis to returning filers and independent students, we find even less evidence of negative impacts on enrollment and state aid receipt.

While we find evidence of verification negatively impacting state aid receipt, the evidence of the negative impact on enrollment is extremely small. However, this finding does not contradict the literature on how financial aid affects enrollment. Previous studies have found an average impact of $1,000 of financial aid increasing enrollment by roughly 2 to 3pp (Nguyen et al., 2019). Given that we find that verification reduces state aid receipt by 5pp (or one-twentieth of the expected treatment effect of receiving financial aid), it is not surprising that we do not find a detectable effect

[36]The covariates include gender, first-generation status, dependency status, year in college, auto-zero EFC, simplified need test, EFC, academic year, and a set of dummies indicating institutions listed on the FAFSA form.

on enrollment. Additional analysis suggests that verification leads to a loss of $118 in the maximum expected Pell Grant and a $168 loss in the maximum expected Cal Grant, which if applicable would suggest enrollment would decline less than a percentage point, which falls within our estimated treatment effect bounds.

Our findings on the impacts of verification do not align with previous studies, which typically show large negative impacts of verification on enrollment in the range of 2 to 6 percentage points (Wiederspan, 2019; Holzman & Hanson, 2020; Lee et al., 2021). One explanation might be due to differences in data construction and validity. For example, previous studies usually rely on a proxy of income status, such as using the median income from the applicant's census tract or self-reported family income categorized into discrete bins. In contrast, we use the original and exact income variable from the FAFSA form, which likely matches more closely to what is used for verification purposes. The second reason for the disagreement between this paper and previous studies might be the specific California context. Although we can list any number of potential differences between state higher education systems, one worthy consideration is that California has the lowest tuition for in-state two-year institutions in the U.S., along with other aid programs unobserved in our data, such as the Community College Promise Grant.[37] Considering the range of moderating variables that can affect the relationship between verification and enrollment, reproducing our results in other state contexts seems well warranted. Yet we perform one replication exercise, which applies the same specification to California as was performed in Iowa, and show that in this case our results differ due to the methodology of the estimation strategy and not contextual differences (Wiederspan, 2019).

Finally, the results should be interpreted in light of potential limitations in our approach. First, any matching approach may not observe the necessary variables or correctly model the exact relationship between inputs and outcomes. We provide some additional validity to our matching approach by showing that matching on variables observed by the Education Department also leads to significant convergence on variables that are not observed, such as GPA and high school characteristics. In addition, our results are robust across a large number of alternate matching approaches. A second limitation is that we cannot observe federal aid receipt, and so cannot say whether the null result on enrollment is related to any changes in verification's impact on federal grants or loans. We do show via simulation that overall changes to financial aid tend to be relatively muted, but a project that could include these data could help illuminate some of these potential pathways.

If verification leads to little change in enrollment or payments but requires significant expenditures in time and energy on the part of students and college staff, then we might question the usefulness of this approach. As previously documented by Guzman-Alvarez & Page (2021), verification is a cumbersome process affecting millions of students each year, and they estimate it

[37] `https://nces.ed.gov/programs/digest/d19/tables/dt19_330.20.asp`.

imposes $500 million in annual compliance costs. This is also in the context of upcoming changes via the FAFSA Simplification Act, which will decrease the number of primary questions from 108 to a maximum of 36. At this time, the Education Department has not identified how verification will change as a result, or whether it will need to change at all. As the federal government moves toward easing administrative burdens through a shorter FAFSA, revisiting the verification process is one key process to re-evaluate. We show that income and EFC values changed for about 44% and 63% of students who were subject to verification and updated their information. Yet our simulated Pell Grant amount declines by only $200 on average, with significant variance showing students with both large losses and large gains in their estimated grant aid receipt. One potential way to improve this process is to shift more of the burden of verification to the federal government through improved data linkages, such as the Data Retrieval Tool, rather than placing more burdens on students. The federal government could also lower verification rates through an improved algorithm, which the Education Department reported they have done in recent years (AlQaisi et al., 2020). Given that many federal agencies, such as the IRS, perform audits on many fewer individuals while still maintaining an effective enforcement mechanism (Boning et al., 2020), there seems to be significant room to relieve this burden on students and colleges. It may be possible to lower verification rates for students even further with intermittent audits of college practices, which leaves in place an enforcement mechanism that can improve compliance (e.g., Telle (2013)).

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Tables

Table 1: Balance Table

	Original Sample			Entropy Balancing	
	Treatment	Control	Difference	Control	Difference
FAFSA Variable (Included in Matching)					
Parents are Married	0.564	0.457	0.107***	0.564	–0.000
	(0.496)	(0.498)	[0.002]	(0.496)	[0.002]
Have Filed Tax Return	0.610	0.696	–0.086***	0.610	–0.000
	(0.488)	(0.460)	[0.002]	(0.488)	[0.002]
Average Gross Income ($1,000)	44.531	22.054	22.477***	44.529	0.002
	(21.738)	(15.962)	[0.078]	(21.739)	[0.089]
Total Income Number ($1,000)	44.866	22.684	22.182***	44.864	0.002
	(21.647)	(16.162)	[0.078]	(21.649)	[0.089]
Total Allowance ($1,000)	36.395	23.870	12.525***	36.394	0.002
	(16.108)	(15.196)	[0.065]	(15.576)	[0.065]
Income Tax Paid ($1,000)	2.189	0.367	1.821***	2.189	0.000
	(7.498)	(2.204)	[0.021]	(7.498)	[0.031]
Available Income ($1,000)	8.471	–1.186	9.657***	8.471	0.001
	(12.840)	(8.350)	[0.044]	(12.848)	[0.053]
Number of Family Members	4.582	4.190	0.392***	4.582	0.000
	(1.556)	(1.540)	[0.006]	(1.556)	[0.006]
EFC ($1,000)	1.707	0.288	1.419***	1.707	0.000
	(1.610)	(0.851)	[0.005]	(1.610)	[0.007]
Zero EFC	0.251	0.790	–0.539***	0.251	–0.000
	(0.433)	(0.407)	[0.002]	(0.433)	[0.002]
Days from Application Cycle Opened	73.417	80.878	–7.461***	73.414	0.003
	(64.162)	(66.660)	[0.273]	(64.161)	[0.264]
FAFSA Variable (Not Included in Matching)					
Female	0.547	0.548	–0.001	0.539	0.008***
	(0.498)	(0.498)	[0.002]	(0.498)	[0.002]
Citizen	0.957	0.936	0.022***	0.957	0.000
	(0.202)	(0.245)	[0.001]	(0.202)	[0.001]
Age	18.280	18.324	–0.043***	18.286	–0.005**
	(0.649)	(0.720)	[0.003]	(0.665)	[0.003]
High School Diploma	0.986	0.981	0.005***	0.984	0.002***
	(0.117)	(0.136)	[0.001]	(0.126)	[0.001]
Parent is Single	0.160	0.221	–0.061***	0.157	0.003**
	(0.367)	(0.415)	[0.002]	(0.364)	[0.002]
Other Marital Status	0.275	0.322	–0.047***	0.278	–0.003
	(0.447)	(0.467)	[0.002]	(0.448)	[0.002]
Will File Tax Return	0.349	0.167	0.182***	0.341	0.007***
	(0.477)	(0.373)	[0.002]	(0.474)	[0.002]
Won't File Tax Return	0.041	0.137	–0.096***	0.048	–0.007***
	(0.198)	(0.343)	[0.001]	(0.214)	[0.001]
Simplified Needs Test	0.445	0.804	–0.358***	0.431	0.014***
	(0.497)	(0.397)	[0.002]	(0.495)	[0.002]
Auto-zero EFC	0.142	0.545	–0.404***	0.168	–0.026***
	(0.349)	(0.498)	[0.002]	(0.374)	[0.001]
Untaxed Income ($1,000)	0.582	0.712	–0.130***	0.662	–0.080***
	(3.404)	(4.960)	[0.018]	(3.661)	[0.015]
Additional Financial Information ($1,000)	0.248	0.085	0.164***	0.328	–0.080***
	(2.915)	(0.933)	[0.008]	(2.795)	[0.012]
Zero Net Worth	0.959	0.986	–0.027***	0.956	0.003***
	(0.198)	(0.117)	[0.001]	(0.204)	[0.001]
Net Worth ($1,000)	2.741	1.030	1.711***	3.313	–0.572***
	(19.998)	(12.609)	[0.067]	(22.089)	[0.087]
Asset Protection Allowance ($1,000)	9.618	3.341	6.277***	9.787	–0.169***
	(9.688)	(7.317)	[0.035]	(9.643)	[0.040]
Total Parent Contribution ($1,000)	2.404	0.377	2.027***	2.423	–0.019*
	(2.679)	(1.217)	[0.008]	(2.659)	[0.011]
Number of Family Members in College	1.493	1.376	0.117***	1.553	–0.061***
	(0.714)	(0.646)	[0.003]	(0.757)	[0.003]

Table 1: Continued

	Original Sample			Entropy Balancing	
	Treatment	Control	Difference	Control	Difference
High School GPA					
GPA Data Missing	0.086	0.094	–0.007***	0.086	0.001
	(0.281)	(0.292)	[0.001]	(0.280)	[0.001]
Highschool GPA	2.802	2.737	0.066***	2.819	–0.016***
	(0.862)	(0.894)	[0.004]	(0.860)	[0.004]
High School Characteristics					
Regular School	0.766	0.755	0.011***	0.763	0.004**
	(0.423)	(0.430)	[0.002]	(0.426)	[0.002]
Non-regular School	0.033	0.042	–0.009***	0.033	0.000
	(0.178)	(0.201)	[0.001]	(0.178)	[0.001]
Missing School	0.187	0.184	0.003*	0.189	–0.002
	(0.390)	(0.388)	[0.002]	(0.392)	[0.002]
Not Report School	0.014	0.018	–0.005***	0.016	–0.002***
	(0.116)	(0.133)	[0.001]	(0.124)	[0.000]
Title I School	0.704	0.754	–0.050***	0.700	0.004**
	(0.456)	(0.431)	[0.002]	(0.458)	[0.002]
Charter School	0.086	0.097	–0.011***	0.092	–0.006***
	(0.281)	(0.296)	[0.001]	(0.289)	[0.001]
Magnet School	0.147	0.154	–0.006***	0.146	0.001
	(0.354)	(0.361)	[0.002]	(0.353)	[0.002]
Free or Reduced Priced Lunch	0.479	0.507	–0.028***	0.474	0.006***
	(0.324)	(0.332)	[0.001]	(0.325)	[0.001]
Share of White	0.213	0.192	0.021***	0.220	–0.007***
	(0.205)	(0.200)	[0.001]	(0.210)	[0.001]
Share of African American	0.062	0.065	–0.003***	0.062	–0.000
	(0.078)	(0.084)	[0.000]	(0.077)	[0.000]
Share of Hispanic	0.565	0.591	–0.025***	0.556	0.010***
	(0.265)	(0.263)	[0.001]	(0.265)	[0.001]
Share of Asian	0.124	0.119	0.005***	0.125	–0.001**
	(0.157)	(0.158)	[0.001]	(0.159)	[0.001]
Share of American Indian and Alaska Native	0.005	0.005	0.000	0.006	–0.000***
	(0.017)	(0.016)	[0.000]	(0.017)	[0.000]
Share of Native Hawaiians and Pacific Islanders	0.006	0.005	0.000***	0.006	–0.000
	(0.008)	(0.008)	[0.000]	(0.008)	[0.000]
Share of Two or More Races	0.025	0.024	0.002***	0.026	–0.001***
	(0.028)	(0.028)	[0.000]	(0.029)	[0.000]
Share of Female	0.500	0.498	0.002***	0.500	0.000
	(0.047)	(0.051)	[0.000]	(0.048)	[0.000]
Application Portfolio					
List CC on FAFSA Form	0.543	0.571	–0.028***	0.535	0.008***
	(0.498)	(0.495)	[0.002]	(0.499)	[0.002]
List CSU on FAFSA Form	0.500	0.491	0.008***	0.495	0.005**
	(0.500)	(0.500)	[0.002]	(0.500)	[0.002]
List UC on FAFSA Form	0.296	0.301	–0.005**	0.298	–0.002
	(0.457)	(0.459)	[0.002]	(0.457)	[0.002]
List Other Colleges on FAFSA Form	0.226	0.225	0.001	0.231	–0.005***
	(0.418)	(0.417)	[0.002]	(0.422)	[0.002]
Number of Observations	100,232	136,013		136,013	

Note: The sample are applicants who are first-time, dependent, Pell-eligible, and submitting before August. Summary statistics of gender, marital status, tax return status, GPA, and Cal Grant payment are reported ignoring the missing value. The auto-zero EFC cutoff was $25,000 for AGI in all application cycles. The pell-grant eligible cut-off was $5,234 and $5,328 for EFC in the 2016 to 2017 application cycles, respectively. The simplified needs test cutoff was 50,000 for total income in all application cycles. Standard deviations are reported in parentheses. Standard errors are reported in squared brackets. $***p < 0.01$, $**p < 0.05$, $*p < 0.1$

Table 2: The Effect of Getting Verification: OLS and Entropy Balancing Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FAFSA	Enrollment (In-State)			Cal Grant Receipt			
	Any Update	Public Any	Public 2-Year	Public 4-Year	Any	Public 2-Year	Public 4-Year	Private
Panel A: OLS Without Covariates								
Verification	0.259***	–0.005**	–0.006*	0.001	–0.148***	–0.120***	–0.031***	0.002**
	(0.003)	(0.002)	(0.003)	(0.003)	(0.006)	(0.003)	(0.003)	(0.001)
Control Mean	0.497	0.752	0.470	0.282	0.521	0.230	0.258	0.032
Panel B: Entropy Balancing								
Verification	0.223***	–0.001	0.007	–0.008*	–0.048***	–0.026***	–0.019***	–0.004
	(0.006)	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.004)	(0.003)
Control Mean	0.542	0.744	0.455	0.289	0.416	0.136	0.244	0.037
Observations				236,245				

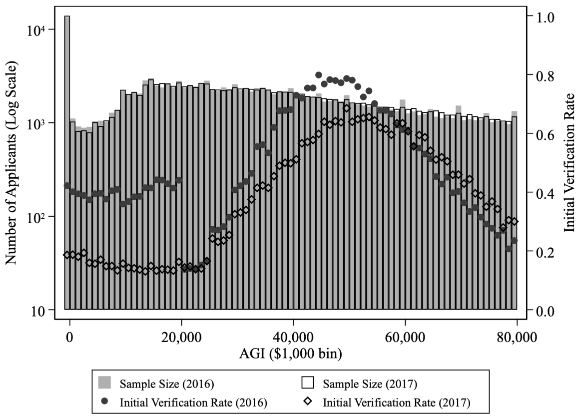
Note: Standard error cluster at high school by cohort level in parentheses. The samples are applicants who are first-time, dependent, Pell-eligible, and submitting before August. Public 2-year refers to the California Community College (CCC) System. Public 4-year refers to the California State University (CSU) System and the University of California (UC) system. The treatment variable is got verification in the first transaction. All regressions include application cycle fixed effect. Entropy balancing (EB) includes parental marital status, tax filing status, number of family members, AGI, total income number, total allowance, income tax paid, EFC, dummies indicating zero EFC, number of days of submission from application open, submit FAFSA on the weekend, dummies indicating the week of FAFSA submission. The control means in Panel B are weighted by EB weights.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table 3: The Long-run Effect of Getting Verification: Entropy Balancing Results

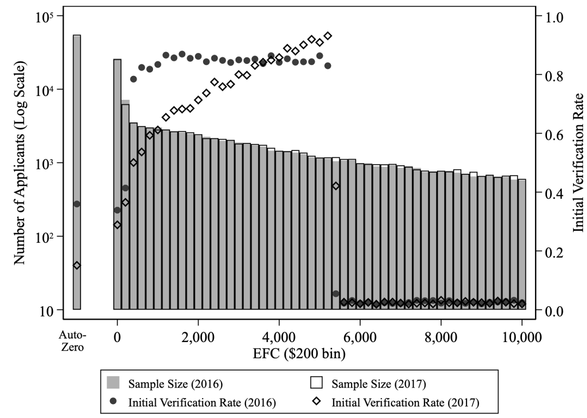
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Enrollment				Cal Grant Receipt			
Years from First Submission	1	2	3	4	1	2	3	4
Panel A: In-state Public 2-Year								
Verification	0.007	0.008	0.000	–0.005	–0.026***	–0.010***	–0.004***	–0.005***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.003)	(0.002)	(0.001)	(0.001)
Control Mean	0.455	0.424	0.346	0.248	0.136	0.084	0.046	0.021
Panel B: In-state Public 4-Year								
Verification	–0.008*	–0.010**	–0.005	–0.002	–0.019***	–0.014***	–0.012***	–0.010**
	(0.005)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Control Mean	0.289	0.240	0.224	0.236	0.244	0.210	0.203	0.207
Panel C: Any In-state Public								
Verification	–0.001	–0.002	–0.004	–0.007	–0.044***	–0.023***	–0.016***	–0.015***
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.004)	(0.004)	(0.005)
Control Mean	0.744	0.664	0.570	0.484	0.379	0.295	0.249	0.228
Observations	236,245				236,245			

Note: Standard error cluster at high school by cohort level in parentheses. The samples are applicants who are first-time, dependent, Pell-eligible, and submitting before August. Public 2-year refers to the California Community College (CCC) System. Public 4-year refers to the California State University (CSU) System and the University of California (UC) system. The treatment variable is got verification in the first transaction. All regressions use EB weight (with the same process as Table 2) and include application cycle fixed effect. Year 1 refers to the academic year of the FAFSA application cycle, and year 2 refers to the next year, and so on. The control means are weighted by EB weights.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

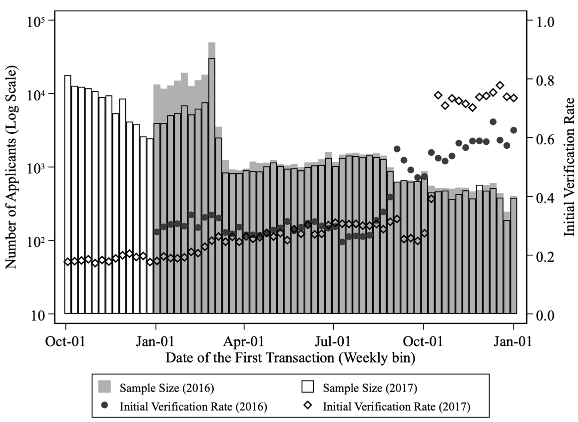
Figures



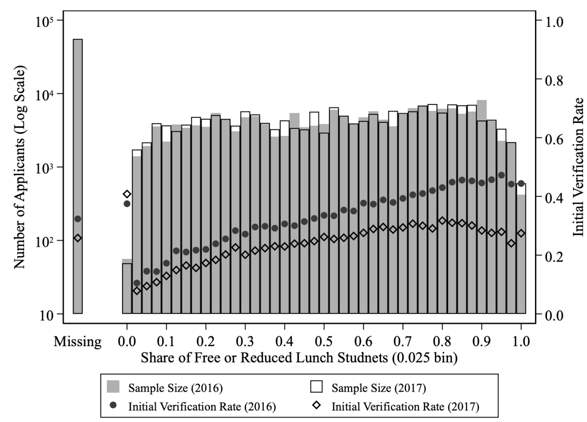
(a) Adjusted Gross Income (AGI)



(b) Expected Family Contribution (EFC)



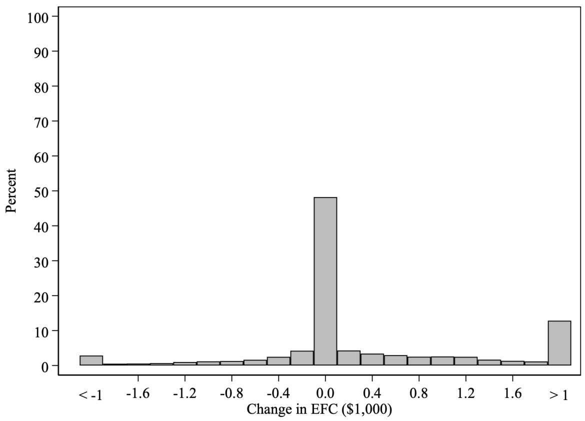
(c) FAFSA Submission Date



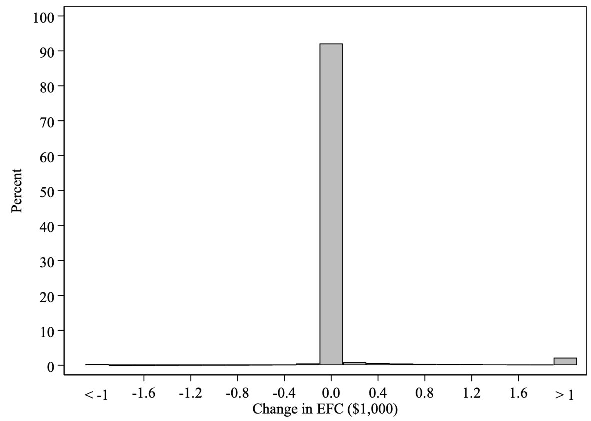
(d) High School Free or Reduced Lunch Proportion

Figure 1: Verification Rate and Sample Size

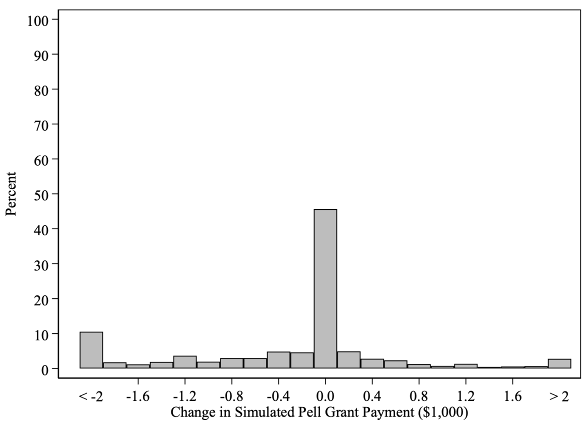
Note: The sample are first-time filers, who are first-time freshmen and dependent. The number of observations is 460,372. The auto-zero EFC cutoff was $25,000 for AGI in 2016 and 2017 application cycle. The pell-grant eligible cut-off was $5,234 in 2016 application cycle and $5,328 for EFC in 2017 application cycle. The 2016 application opened on January 1, 2016, while the 2017 application cycle opened on October 1, 2016. The Cal Grant Application deadline is March 2.



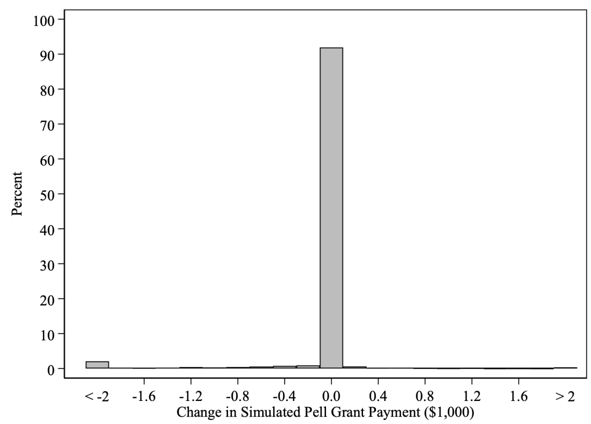
(a) Change in EFC, Verification Group



(b) Change in EFC, Non-Verification Group



(c) Change in Pell-Grant, Verification Group



(d) Change in Pell-Grant, Non-Verification Group

Figure 2: Change in EFC and Simulated Pell-Grant Payment Across First and Last Transactions

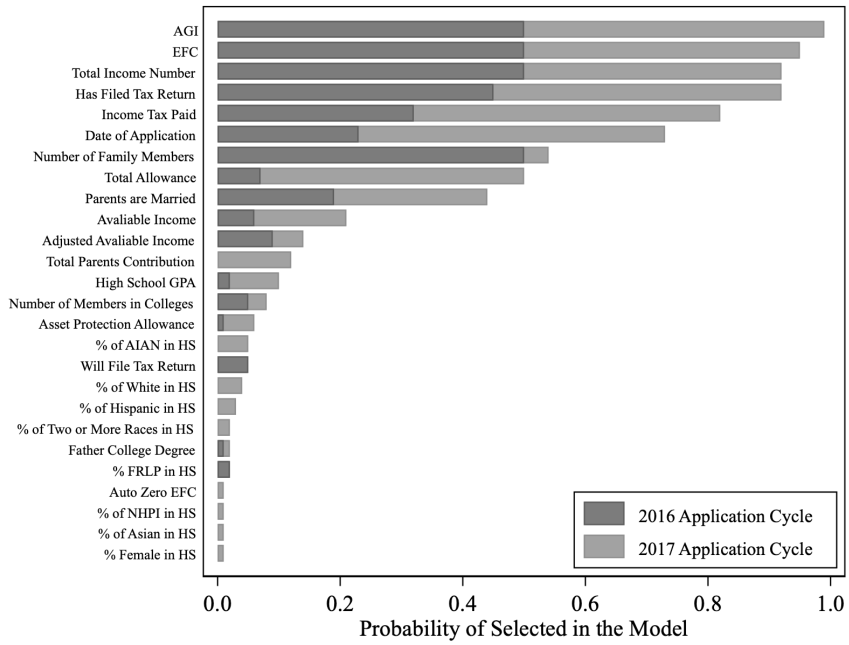
Note: The sample are applicants who are first-time, dependent, Pell-eligible, and submitting before August, and have multiple transactions. The numbers of observations are 76,501 for Figure 2a and 2c, and 62,279 for Figure 2b and 2d. The sample in this figure are people who did not submit FAFSA previously, are dependent, first-time freshmen, Pell Grant eligible in the first transaction, and have multiple transactions. The simulated Pell Grant payment is calculated with EFC and based on full-time enrollment. The amount is for one academic year.

Appendix A: Methodology Appendix

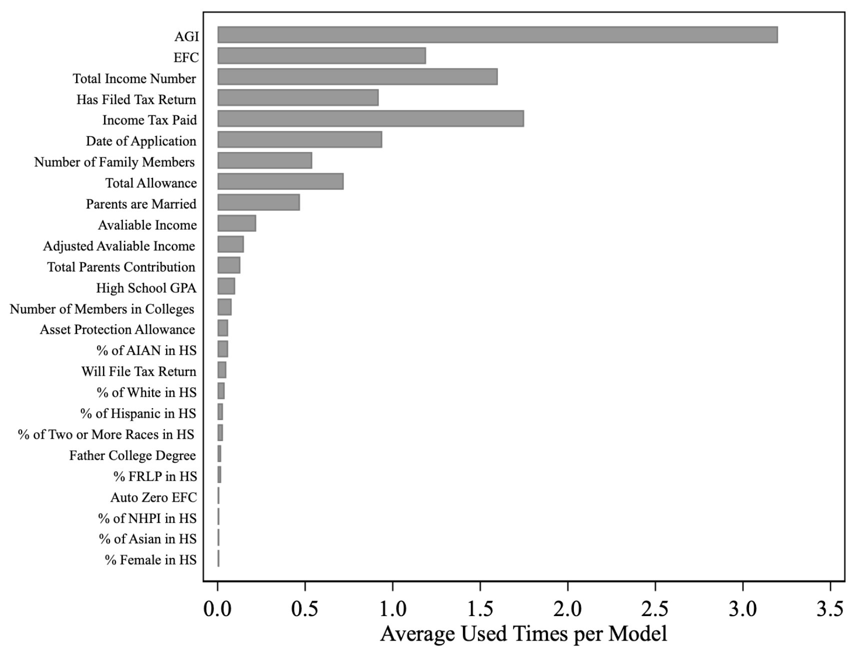
The idea of Entropy Balancing (EB) is to search for a set of weights for the control group to ensure that the treatment and control groups are balanced in the specified variables, potentially along multiple moments, and at the same time retain the information as much as possible (Hainmueller, 2012; Watson & Elliot, 2016). As shown in Figure 1, the relationship between verification and background variables, such as family income, varies across years. As a result, we conduct the matching process separately for the 2016 and 2017 application cycles. In the EB matching process, we include whether parents are married, whether parents have filed tax returns, AGI, total income number, total allowance, available income, income tax paid, number of family members, EFC, dummy indicating zero EFC, dates of application (as numbers of days from application open), whether they submitted the FAFSA on the weekend, and a series of dummies indicating the week of FAFSA submission. We include the first, second, and third moments in the matching process for all the variables. We only include the selected variables (as determined by our machine learning approach and demonstrated in Figure A1) in the main specification. Though Table 1 shows some imbalance of non-include variables among the treatment and control groups, the differences were reduced compared to the results before matching. Furthermore, the magnitudes of the differences are quite small. However, in later analysis, we include all FAFSA variables as well as GPA and high school characteristics to test for robustness.

Figure A2 demonstrates that our machine learning models with the selected variables have a good performance. We first randomly select 10,000 (about 7% of our samples) observations as the training sample. Then we use the variables included in the EB process to perform 100 times regression tree analysis (i.e., random forest) to predict the verification rate. Finally, we apply the prediction to the non-training samples and compare the predicted verification rate with the actual verification rate. Figure A2 shows that the predicted verification rate with the actual verification rate almost matched the actual verification throughout the whole distribution.[38] In general, though we only choose a small set of variables to include in our matching process, these variables have good predicted power for the verification status.

[38]To quantify the performance, we perform the machine learning algorithm to predict a binary outcome (instead of a continuous probability) and then calculate the "accuracy rate" by comparing the matched prediction and actual results. This approach provides an accuracy rate of over 85%. We also calculate the "pseudo-R-squared" by computing the "sum squared error (SSE)" (the distance from the predicted verification rate to the actual verification rate) and "sum of squares regression (SSR)" (the distance from predicted verification rate to mean verification). This approach provides a pseudo-R-squared of 0.57 to 0.61 (varies by application years and formula applied).



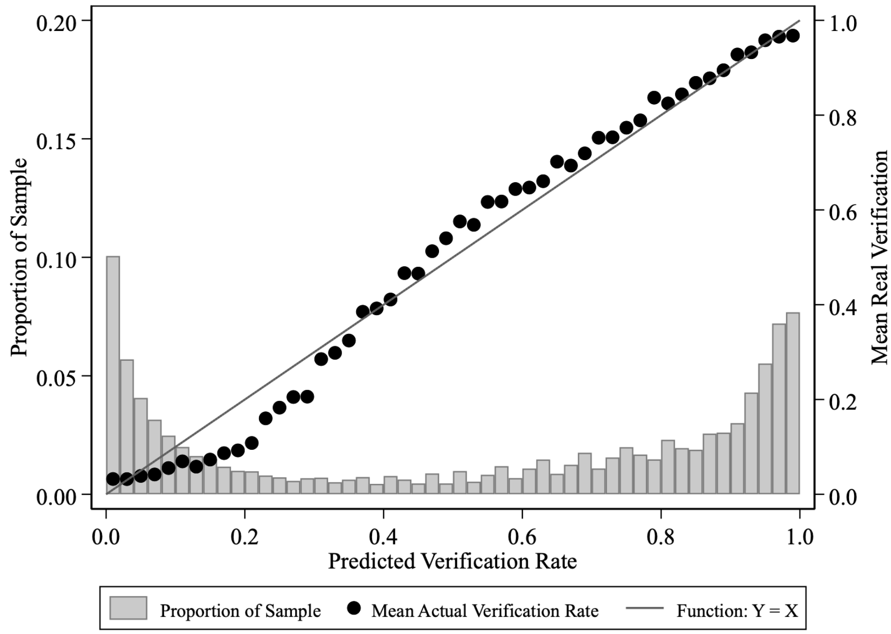
(a) Number of Times Selected in Prediction Models



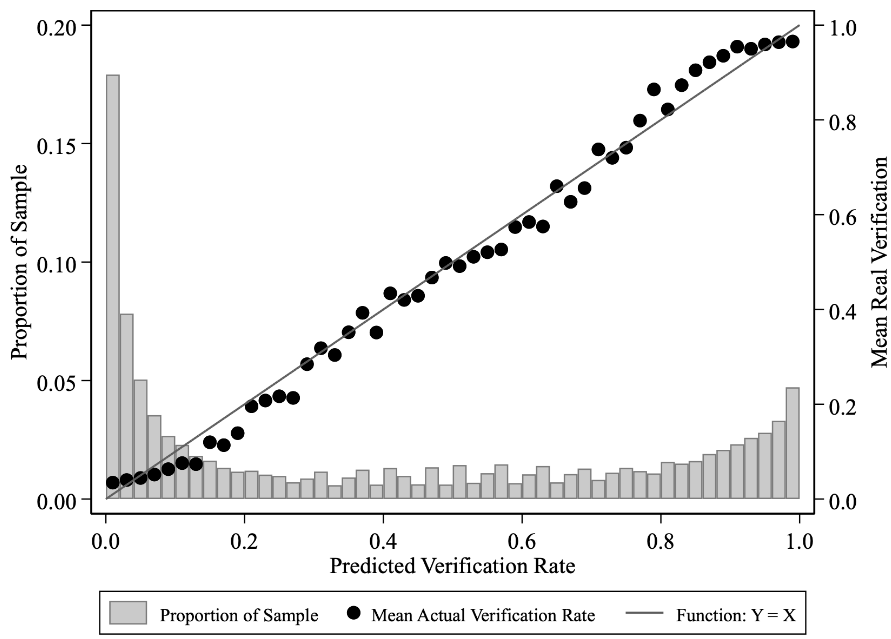
(b) Average Used Times in Prediction Models

Figure A1: Use Machine Learning Approach to Predict Verification Rate

Note: The sample are applicants who are first-time, dependent, Pell-eligible, and submitting before August. We conduct 50 times of regression tree for each 2016 and 2017 application cycle, respectively. In each regression tree analysis, we randomly select 10,000 observations as the training sample.



(a) Year 2016



(b) Year 2017

Figure A2: Predicted Verification Rate and Actual Verification Rate

Note: The samples are applicants who are first-time, dependent, Pell-eligible, and submitting before August. We conduct 100 times of regression tree predictions for each 2016 and 2017 application cycle, respectively. We randomly select 10,000 observations as the training sample. The predicted and actual verification rate is only calculated for the testing sample (those not in the training sample).

Appendix B: Robustness Check and Additional Results

Table B1: Change in FAFSA Variables between First and Last Transactions

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Treatment Group (Got Verification)				Control Group (Not Got Verification)			
	First Transaction	Last Transaction	Average Change	% of Changed	First Transaction	Last Transaction	Average Change	% of Changed
FAFSA Variable (Reported by Applicants)								
Female	0.556	0.557	0.002***	0.003	0.560	0.563	0.003***	0.004
	(0.497)	(0.497)	[0.000]		(0.496)	(0.496)	[0.000]	
Citizen	0.956	0.954	–0.002***	0.004	0.932	0.928	–0.004***	0.008
	(0.205)	(0.209)	[0.000]		(0.252)	(0.259)	[0.000]	
Age	18.245	18.245	0.000	0.000	18.275	18.275	0.000	0.000
	(0.571)	(0.572)	[0.000]		(0.614)	(0.615)	[0.000]	
Single	0.156	0.154	–0.002***	0.014	0.218	0.218	0.001***	0.010
	(0.363)	(0.361)	[0.000]		(0.413)	(0.413)	[0.000]	
Married	0.573	0.580	0.007***	0.029	0.465	0.466	0.001***	0.015
	(0.495)	(0.494)	[0.001]		(0.499)	(0.499)	[0.000]	
Other Marital Status	0.271	0.266	–0.005***	0.023	0.318	0.316	–0.002***	0.013
	(0.445)	(0.442)	[0.001]		(0.466)	(0.465)	[0.000]	
Have Filed Tax Return	0.588	0.930	0.342***	0.351	0.658	0.843	0.185***	0.194
	(0.492)	(0.255)	[0.002]		(0.475)	(0.364)	[0.001]	
Will File Tax Return	0.376	0.029	–0.347***	0.348	0.221	0.032	–0.189***	0.190
	(0.484)	(0.168)	[0.002]		(0.415)	(0.176)	[0.001]	
Won't File Tax Return	0.036	0.041	0.005***	0.012	0.122	0.125	0.003***	0.013
	(0.187)	(0.198)	[0.000]		(0.327)	(0.331)	[0.000]	
Number of Family Members	4.577	4.296	–0.281***	0.231	4.178	4.123	–0.054***	0.067
	(1.546)	(1.458)	[0.003]		(1.525)	(1.504)	[0.002]	
Number of Family Members in College	1.507	1.416	–0.092***	0.125	1.375	1.346	–0.029***	0.042
	(0.720)	(0.632)	[0.002]		(0.643)	(0.599)	[0.001]	
ISIR Variable (Determined by the FAFSA Office)								
Dependent	1.000	0.989	–0.011***	0.011	1.000	0.987	–0.013***	0.013
	(0.000)	(0.107)	[0.000]		(0.000)	(0.111)	[0.000]	
Average Gross Income ($1,000)	45.163	46.632	1.469***	0.409	22.474	23.460	0.986***	0.209
	(21.524)	(35.975)	[0.103]		(16.129)	(19.884)	[0.045]	
Zero Net Worth	0.957	0.906	–0.050***	0.059	0.984	0.974	–0.010***	0.012
	(0.204)	(0.292)	[0.001]		(0.124)	(0.158)	[0.000]	
Net Worth ($1,000)	2.960	5.290	2.330***	0.067	1.254	2.359	1.105***	0.014
	(20.807)	(53.071)	[0.173]		(14.277)	(50.891)	[0.176]	
Simplified Needs Test	0.436	0.426	–0.010***	0.080	0.798	0.784	–0.014***	0.038
	(0.496)	(0.495)	[0.001]		(0.401)	(0.411)	[0.001]	
Auto-zero EFC	0.132	0.136	0.004***	0.036	0.539	0.518	–0.021***	0.052
	(0.339)	(0.342)	[0.001]		(0.498)	(0.500)	[0.001]	
Zero EFC	0.238	0.232	–0.006***	0.094	0.786	0.757	–0.029***	0.054
	(0.426)	(0.422)	[0.001]		(0.410)	(0.429)	[0.001]	
EFC ($1,000)	1.738	2.686	0.948***	0.586	0.312	0.526	0.214***	0.094
	(1.605)	(6.898)	[0.023]		(0.907)	(3.604)	[0.013]	
Federal and State Aid Eligibility								
Pell Grant Eligible	1.000	0.902	–0.098***	0.098	1.000	0.989	–0.011***	0.011
	(0.000)	(0.298)	[0.001]		(0.000)	(0.104)	[0.000]	
Pell Grant Amount (Simulated, $1,000)†	4.118	3.734	–0.384***	0.551	5.562	5.468	–0.094***	0.090
	(0.799)	(0.974)	[0.002]		(0.452)	(0.544)	[0.001]	
Cal Grant B Eligible	0.434	0.404	–0.030***	0.088	0.683	0.669	–0.013***	0.020
	(0.496)	(0.491)	[0.001]		(0.465)	(0.470)	[0.000]	
Cal Grant A Eligible	0.462	0.448	–0.014***	0.018	0.439	0.436	–0.003***	0.004
	(0.499)	(0.497)	[0.000]		(0.496)	(0.496)	[0.000]	
Cal Grant Amount (Simulated, $1,000)‡	6.046	5.849	–0.197***	0.050	5.925	5.885	–0.039***	0.010
	(5.945)	(5.954)	[0.006]		(5.837)	(5.842)	[0.003]	
Number of Observations		81,933				77,808		

Note: Standard deviation in parentheses. Standard error in squared brackets. The sample are applicants who are first-time, dependent, Pell-eligible, submitting before August, and have multiple transactions. The auto-zero EFC cutoff was $25,000 for AGI in the 2016 and 2017 application cycles. The pell-grant eligible cut-off was $5,234 in the 2016 application cycle and $5,328 for EFC in the 2017 application cycle. The Cal Grant income eligibility is based on the number of family members, total income number, and net worth. Cal Grant B eligible are people who with low-income, GPA above 2.0, and submit FAFSA before March 2. Cal Grant A eligible are people of low-income or middle-low-income, GPA above 3.0, and submit FAFSA before March 2.

† Pell Grant payment is simulated with EFC, assuming that the student enrolls full-time. The amount is for one academic year.

‡ Maximum Cal Grant payment is simulated with Cal Grant A and B eligibility, assuming that the student enrolls in UC full-time. The amount is for an academic year.

$***p < 0.01, **p < 0.05, *p < 0.1$

Table B2: The Effect of Getting Verification on (Simulated) Financial Aid Amount

	(1)	(2)	(3)	(4)	(5)
	Simulated Pell Amount		Simulated Cal Grant Amount		Observed Cal
	First Row	Final Row	First Row	Final Row	Grant Amount
Panel A: OLS Without Covariates					
Verification	–1,464.964***	–1,713.558***	171.491***	41.789	–250.431***
	(28.590)	(30.674)	(49.910)	(49.641)	(30.001)
Control Mean	5,587.424	5,533.928	5554.268	5531.754	2485.037
Panel B: Entropy Balancing					
Verification	–0.808	–235.070***	–51.264	–167.610***	–196.515***
	(18.300)	(21.618)	(62.395)	(62.272)	(40.114)
Control Mean	4,152.110	4,072.464	5703.948	5658.904	2417.463
Observations			236,245		

Note: Standard error cluster at high school by cohort level in parentheses. The samples are applicants who are first-time, dependent, Pell-eligible, and submitting before August. We simulate changes in Pell Grant receipt based on the observed EFC reported in our FAFSA data, assuming that the student enrolls full-time for an academic year. We simulated changes in Cal Grant payments assuming a student enrolls full-time for an academic year; these payments cover full tuition and fees at the CSU or UC, or a cash payment of roughly $1,500 at the community college. In both cases we chose full-time to enrollment to create an upper bound of the effect of verification on grant aid payments. The treatment variable is got verification in the first transaction. All regressions use EB weight (with the same process as Table 2) and include application cycle fixed effect. The control means in Panel B are weighted by EB weights.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B3: Robustness Check—OLS with Covariates and Other Entropy Balancing Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FAFSA	Enrollment (In-State)			Cal Grant Receipt			
	Any Update	Public Any	Public 2-Year	Public 4-Year	Any	Public 2-Year	Public 4-Year	Private
Panel A: OLS (With Covariates)								
Verification	0.253***	–0.012***	0.002	–0.014***	–0.068***	–0.045***	–0.021***	–0.002**
	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
Control Mean	0.497	0.752	0.470	0.282	0.521	0.230	0.258	0.032
Panel B: EB (With Covariates)								
Verification	0.226***	–0.007*	0.004	–0.011***	–0.050***	–0.028***	–0.020***	–0.002
	(0.004)	(0.003)	(0.004)	(0.003)	(0.003)	(0.002)	(0.003)	(0.002)
Control Mean	0.542	0.744	0.455	0.289	0.416	0.136	0.244	0.037
Panel C: EB (With Full Variables in Matching Process)								
Verification	0.226***	–0.000	0.007	–0.007	–0.051***	–0.031***	–0.016***	–0.003
	(0.006)	(0.006)	(0.006)	(0.005)	(0.005)	(0.003)	(0.004)	(0.003)
Control Mean	0.540	0.743	0.456	0.287	0.420	0.141	0.242	0.037
Observations	236,245							

Note: Standard error cluster at high school by cohort level in parentheses. The samples are applicants who are first-time, dependent, Pell-eligible, and submitting before August. Public 2-year refers to the California Community College (CCC) System. Public 4-year refers to the California State University (CSU) System and the University of California (UC) system. The treatment variable is got verification in the first transaction. All regressions include the application cycle fixed effect. Panel A and B covariates include gender, citizenship status, birthdate, parental marital status, parental education level, tax filing status, number of family members, number of family members in colleges, AGI, total income number, total allowance, income tax paid, EFC, dummies indicating zero EFC, auto-zero EFC status, simplified need formula status, available income, adjusted available income, untaxable income, untaxable pension, IRA payment, interest income, net worth, APA amount, DNW amount, total contribution, number of days of submission from application open, submit FAFSA on the weekend, dummies indicating the week of FAFSA submission, high school GPA, high school fixed effect, and colleges listed on FAFSA. Panel C includes all the above variables in the EB matching process.

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B4: Subgroup Analysis and Additional Samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FAFSA	Enrollment (In-State)			Cal Grant Receipt			
	Any Update	Public Any	Public 2-Year	Public 4-Year	Any	Public 2-Year	Public 4-Year	Private
Panel A: Main Sample — Submit Before March 2								
Verification	0.212***	–0.002	0.004	–0.006	–0.043***	–0.021***	–0.018***	–0.004
	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)	(0.003)	(0.005)	(0.003)
Control Mean	0.581	0.759	0.430	0.329	0.466	0.147	0.277	0.043
Observations					204,030			
Panel B: Main Sample — Submit After March 2								
Verification	0.275***	0.010	0.011	–0.000	0.001	0.001	0.000*	0.000
	(0.016)	(0.018)	(0.018)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)
Control Mean	0.306	0.643	0.638	0.004	0.007	0.007	0.000	0.000
Observations					32,214			
Panel C: Independent, First-time, Pell-eligible								
Verification	0.134***	–0.016	–0.021	0.005	0.009	0.001	0.005	0.002**
	(0.013)	(0.017)	(0.018)	(0.006)	(0.006)	(0.003)	(0.005)	(0.001)
Control Mean	0.361	0.450	0.426	0.024	0.066	0.045	0.018	0.003
Observations					110,574			
Panel D: Returning Filers but Did Not Get Verification Last Year								
Verification	0.359***	0.007	0.010	–0.004	–0.013	–0.006***	–0.005	–0.002
	(0.012)	(0.010)	(0.012)	(0.008)	(0.011)	(0.002)	(0.011)	(0.002)
Control Mean	0.373	0.729	0.436	0.293	0.286	0.061	0.195	0.030
Observations					208,958			
Panel E: Returning Filers Who Got Verification Last Year								
Verification	0.357***	0.001	0.007	–0.006	–0.006	–0.005***	–0.002	0.000
	(0.005)	(0.004)	(0.006)	(0.004)	(0.004)	(0.002)	(0.004)	(0.001)
Control Mean	0.374	0.758	0.422	0.336	0.326	0.057	0.237	0.033
Observations					164,496			

Note: Standard error cluster at high school by cohort level in parentheses for Panel A, C, D, and E. Standard error cluster at the zip code level in parentheses for Panel B. Panel A to C include the 2016 and 2017 application cycles. The sample in Panel A to C are applicants who are first-time, Pell-eligible, and submitting before August. The sample in Panel D and E only include people who submit FAFSA in both the 2016 and 2017 application cycles and are dependent and Pell-eligible. All regressions use EB weight (with the same process as Table 2) and include application cycle fixed effect. The control means are weighted by EB weights.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B5: Subgroup Analysis by Initial EFC

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Pell Eligibility and Amount			Cal Grant Eligibility and Amount			Enrollment	Cal Grant
	EFC	Eligible	Simulated Amount	Total Income	Eligible	Simulated Amount	In-state Public	Receipt
Panel A: Initial EFC $>$ Pell Cutoff								
Verification	907.922	0.013***	39.046***	–723.604	–0.004	–55.912	0.000	–0.002
	(1,205.202)	(0.004)	(15.026)	(4,776.238)	(0.005)	(64.911)	(0.008)	(0.004)
Control Mean	42,559	0.043	170.242	169,573	0.147	1,743	0.496	0.076
Observations				169,603				
Panel B: Initial EFC $>$ 0 & $<$ Pell Cutoff								
Verification	473.589***	–0.049***	–223.578***	568.340	–0.019***	–123.483	0.011	–0.041***
	(79.569)	(0.005)	(28.214)	(632.519)	(0.007)	(85.557)	(0.007)	(0.007)
Control Mean	2,657	0.949	3,496	53,275	0.600	5,877	0.741	0.395
Observations				103,677				
Panel C: Initial EFC = 0								
Verification	294.411***	–0.012***	–212.326***	1,301.856*	–0.013*	–17.269	–0.005	–0.063***
	(89.648)	(0.004)	(24.960)	(670.805)	(0.007)	(89.053)	(0.009)	(0.009)
Control Mean	245.249	0.990	5,742	22,603	0.677	4,725	0.720	0.474
Observations				132,563				

Note: Standard error cluster at high school by cohort level in parentheses.The samples are applicants who are first-time, dependent, and submitting before August. We simulate changes in Pell Grant receipt based on the observed EFC reported in our FAFSA data, assuming that the student enrolls full-time for an academic year. We simulated changes in Cal Grant payments assuming a student enrolls full-time for an academic year; these payments cover full tuition and fees at the CSU or UC, or a cash payment of roughly $1,500 at the community college. In both cases we chose full-time to enrollment to create an upper bound of the effect of verification on grant aid payments. The treatment variable is got verification in the first transaction. All regressions use EB weight (with the same process as Table 2) and include application cycle fixed effect. The control means are weighted by EB weights. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B6: Subgroup Analysis by Application Portfolio

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FAFSA	Enrollment (In-State)			Cal Grant Receipt			
	Any Update	Public Any	Public 2-Year	Public 4-Year	Any	Public 2-Year	Public 4-Year	Private
Panel A: List In-State Public 4-Year but not 2-Year College								
Verification	0.188***	0.008	0.012*	-0.004	-0.033***	-0.004	-0.022**	-0.007
	(0.008)	(0.009)	(0.007)	(0.009)	(0.010)	(0.003)	(0.009)	(0.005)
Observations	85,521	85,521	85,521	85,521	85,521	85,521	85,521	85,521
Control Mean	0.720	0.777	0.166	0.611	0.633	0.054	0.514	0.064
Panel B: List In-State Public 4-Year and 2-year College								
Verification	0.239***	-0.009	0.017	-0.027**	-0.069***	-0.038***	-0.033***	0.002
	(0.011)	(0.008)	(0.011)	(0.010)	(0.012)	(0.008)	(0.010)	(0.003)
Observations	42,946	42,946	42,946	42,946	42,946	42,946	42,946	42,946
Control Mean	0.548	0.847	0.540	0.307	0.478	0.214	0.249	0.015
Panel C: List In-State Public 2-Year but not 4-Year College								
Verification	0.255***	-0.007	-0.008	0.000	-0.060***	-0.060***	-0.000	-0.000
	(0.008)	(0.007)	(0.006)	(0.000)	(0.006)	(0.006)	(0.000)	(0.001)
Observations	89,131	89,131	89,131	89,131	89,131	89,131	89,131	89,131
Control Mean	0.350	0.761	0.760	0.001	0.216	0.212	0.001	0.004

Note: Standard error cluster at high school by cohort level in parentheses. The sample are applicants who are first-time filers, undergraduate, dependent, Pell-eligible, and submitting before August. The treatment variable is got verification in the first transaction. Panel A includes people who either list any in-state public 4-year college(s) (either UC or CSU) on their FAFSA form but do not list any in-state public 2-year college (CC). Panel B includes people who list both in-state public 4-year college(s) (either UC or CSU) and 2-year college(2) (CC). Panel C includes people who either list any in-state public 2-year college(s) (CC) on their FAFSA form but do not list any in-state public 4-year college (either UC or CSU). Some students did not list any in-state public colleges on their FAFSA form (about 8% in our sample) and are excluded from this analysis. All regressions use EB weight (with the same process as Table 2) and include application cycle fixed effect. The control means are weighted by EB weights.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table B7: Robustness Check—Applying Samples and Model in Wiederspan (2019)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FAFSA	Enrollment (In-State)			Cal Grant Receipt			
	Any Update	Public Any	Public 2-Year	Public 4-Year	Any	Public 2-Year	Public 4-Year	Private
Panel A: OLS without Covariates								
Verification	0.089***	–0.040***	–0.006	–0.034***	–0.085***	–0.055***	–0.026***	–0.004***
	(0.014)	(0.009)	(0.005)	(0.005)	(0.008)	(0.004)	(0.004)	(0.001)
Control Mean	0.547	0.601	0.450	0.151	0.244	0.119	0.109	0.017
Panel B: OLS with Wiederspan Covariates								
Verification	0.171***	–0.027***	–0.035***	0.008***	–0.039***	–0.044***	0.005***	0.000
	(0.006)	(0.005)	(0.004)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)
Control Mean	0.547	0.601	0.450	0.151	0.244	0.119	0.109	0.017
Panel C: Entropy Balancing								
Verification	0.158***	0.015*	0.015**	0.001	–0.036***	–0.027***	–0.007***	–0.002***
	(0.008)	(0.008)	(0.007)	(0.002)	(0.003)	(0.002)	(0.002)	(0.001)
Control Mean	0.478	0.545	0.428	0.117	0.198	0.092	0.091	0.016
Observations	982,926							

Note: Standard error cluster at high school by cohort level in parentheses. The sample are applicants who are first-time filers, undergraduate, dependent, Pell-eligible, and submitting before August. The treatment variable is got verification in the first transaction. Panel B includes gender, first-generation status, dependency status, year in college, auto-zero EFC, simplified need test, EFC, academic year, and a set of dummies indicating institutions listed on the FAFSA form. Entropy balancing (EB) includes dependent status, year in college, parental marital status, tax filing status, number of family members, AGI, total income number, total allowance, income tax paid, EFC, dummies indicating zero EFC, number of days of submission from application open, submit FAFSA on weekend, dummies indicating the week of FAFSA submission. The control means in Panel C are weighted by EB weights.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Appendix C: Regression Discontinuity Approach

C.1 Natural Experiment

The 2018 FAFSA application cycle opened on October 1, 2017. Early in the cycle, colleges began to publicly question an unusual "surge" in the verification rate for students, leading to stories in prominent newspapers such as the Washington Post.[39] College staff noted that the verification rate appeared two to three times higher than usual and reported the issue to the ED.

Between December 14 to 15, the ED adjusted the verification selection algorithm, stating that this would lead to a "normalization" of the verification rate.[40] However, ED stated that they would not reprocess any cases for students who have already been selected for verification, thus leaving the elevated verification rate in place for those who had already submitted. Although we do not know the specifics of what led to the elevated verification rate, we show below that there are sharp changes for students who first submitted the FAFSA right before and after this December 15 date.

C.2 Empirical Strategy

C.2.1 Difference-in-Discontinuity

While we do not know the specific reason for the anomalously high verification rates in the early parts of the 2018 application cycle, the adjustment in the algorithm creates a natural experiment that allows us to compare applicants who submitted just before and after December 15 policy change. While we might normally adopt a regression discontinuity (RD) design, using the initial FAFSA submission date as the running variable to identify the impact of being subjected to a higher verification rate, one concern is whether students on either side of the discontinuity are comparable. Although we do not believe that individuals would manipulate their submission date to account for the abnormal selection process, there is still cause for concern that there may be unobservable differences between those below and above the December 15 threshold. One would be if certain types of students are more likely to submit the FAFSA on weekdays (Thursday, December 14) than approach to weekends (Friday, December 15); though we later include day of week fixe effect of students submission, it only captures the overall day of week effect rather than the specific effect

[39]Colleges puzzled by surge in FAFSA verification requests. The Washington Post. November 28, 2017. Available at: `https://www.washingtonpost.com/news/grade-point/wp/2017/11/28/colleges-puzzled-by-surge-in-fafsa-verification-requests/`

[40]The announcement was made in January of 2018. See ED Adjusts Verification Selection Algorithm, Selection Rates to Normalize. NASFAA. January 4, 2018. Available at: `https://www.nasfaa.org/news-item/14035/ED_Adjusts_Verification_Selection_Algorithm_Selection_Rates_to_Normalize`. While the announcement states the adjustment was on December 16/17 weekend, we see in our data that the drop in verification rate happened between December 14 and 15.

on the weekend close to December 15. Another issue is that to accurately estimate the causal impact from a regression discontinuity design, we must correctly specify the functional form of the relationship between the FAFSA submission date and enrollment outcomes, which requires using more observations than just those right at the threshold. Unfortunately, various holidays such as Christmas, New Years, and high school winter breaks occur fairly soon after the policy change, which led to a marked drop in daily applications before a large increase that occurred in early January. We also note that many four-year college applications require submission soon before this December 15 window, which could also affect the functional form of FAFSA submission rates.

Therefore, we combine the difference-in-differences (DD) method with the RD design and adopt a difference-in-discontinuity (diff-in-disc) approach. Specifically, we compare the estimated discontinuity in the 2018 application cycle, when the adjustment happened, with the 2017 application cycle in order to control for the types of students who would typically submit around those December dates. The theoretical assumption is that if there are any differences in the types of students who typically apply at the times around the December 15 cutoff, it would be the same in the 2017 and 2018 cycles. Grembi et al. (2016) and Asatryan et al. (2017) suggest the diff-in-disc approach can help identify the treatment effect around a cutoff even in the presence of other factors that may impact the treatment.

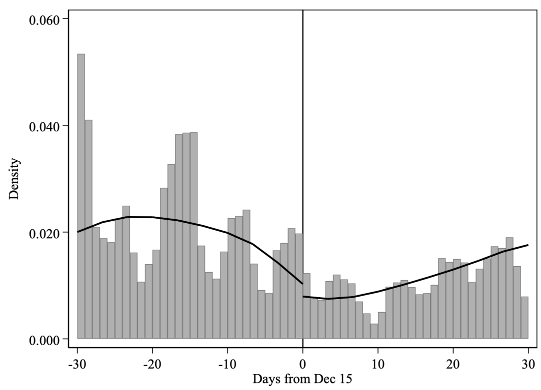
For the diff-in-disc approach, we estimate the following equation:

$$\begin{aligned} Y_{idt} = \alpha_0 + \beta_1 Early_{dt} \times Year_t^{2018} + \beta_2 Early_{dt} + f(Date_{dt}) + Early_{dt} \times f(Date_{dt}) \\ + Year_t^{2018} \times f(Date_{dt}) + Year_t^{2018} \times Early_{dt} \times f(Date_{dt}) + X_{idt} + \theta_t + \varepsilon_{idt} \end{aligned} \tag{1}$$

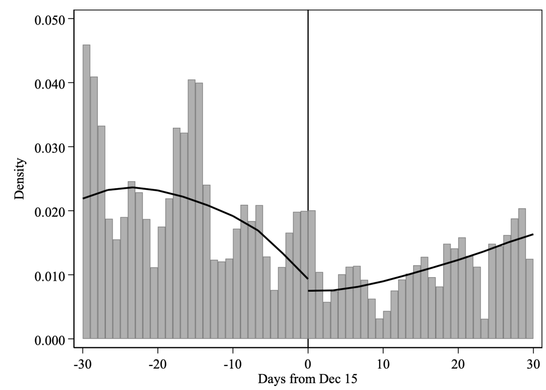
Where Y_{idt} is the outcomes for student i who submitted their FAFSA on date d in application cycle t. $Early_{dt}$ is a dummy variable indicating whether the students submit on and before December 14 of the application cycle. $Year_t^{2018}$ is a dummy variable indicating that the individual submitted in the 2018 application cycle. $f(Date_d)$ is a function of the submission date centered on December 14 for each cycle. β_2 provides an RD estimate for the December 15 cut-off in the 2017 cycle. This estimate would capture any variability associated with the specific date pattern. The key estimate is β_1, which stands for the difference in discontinuity of the December 15 cutoff between the 2018 and 2017 cycles. This estimate could provide a causal estimate for those subjected to the elevated verification algorithm without the confounding effects from the date patterns shared across years.

C.2.2 Validity Test of the Research Design

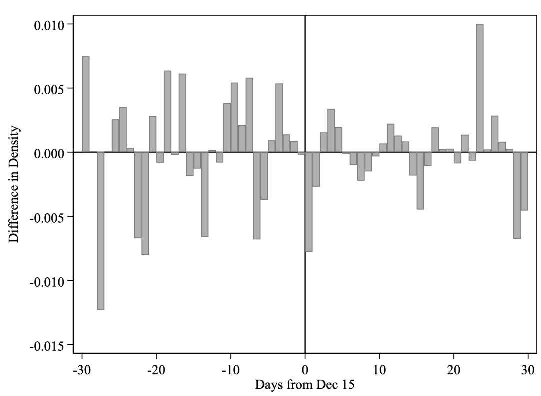
One key assumption of the diff-in-disc approach is that individuals should not be able to (precisely) manipulate the running variable (i.e., the submission date). Based on the assumption, we should expect the density function should be smooth through the cutoff and not show any bunching on each side. Figure C1 plots the distribution of the number of applicants by date of submission. Figure C1a and C1b shows the distribution of the 2018 and 2017 application cycles, respectively. A clear pattern associated with the day of the week and holidays persists. Specifically, there are fewer applicants on weekends compared to weekdays. Besides, students tend to be less likely to submit FAFSA during the winter break. We perform a McCrary manipulation test using the $rddensity$ command proposed by Cattaneo et al. (2020). The estimated manipulation test statistics for the 2018 applicants is -8.10 ($p < 0.001$). And the estimated manipulation test statistics for the 2017 applicants is -7.98 ($p < 0.001$). Though both statistics are significant (implies manipulation behavior exists), the statistics are close.



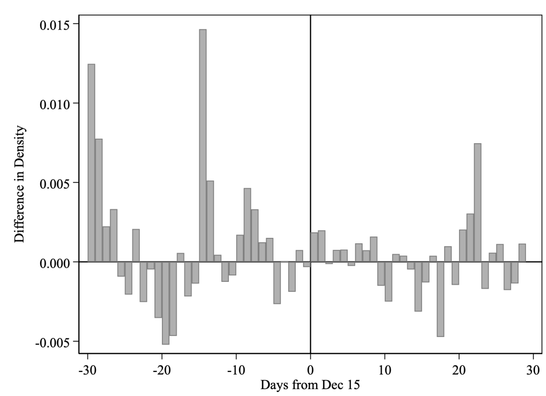
(a) 2018 Cycle



(b) 2017 Cycle



(c) Difference in 2018 and 2017 Cycle (Calendar Date)



(d) Difference in 2018 and 2017 Cycle (Day of Week)

Figure C1: Density Check: Density Distribution of Applicants by Date of Submission

Note: The sample are applicants who are first-time, dependent, Pell-eligible in the 2017 and 2018 application cycle. Panel C shows the difference in density in the 2018 and 2017 cycles by exact calendar date (i.e., compare December 15 in 2017 to December 15 in 2016). Panel D shows the difference in density in the 2018 and 2017 cycle to the nearest calendar date with the same day of the week (i.e., compare December 15 Friday in 2017 to December 16 Friday in 2016).

However, the distribution of the 2018 and 2017 application cycles is quite similar. Figure C1c further displays the difference in density between the 2018 and 2017 cycles. Since the same calendar days are different days of the week in the 2018 and 2017 application cycles, Figure C1d compares the nearest calendar date but the same day of the week between the two cycles instead. Specifically, we show the difference between December 15 Friday, 2017 (2018 cycle) with December 16 Friday, 2016 (2017 cycle). As shown in the figure, the distribution of the difference in density between the two application cycles is smooth.[41]

Another assumption of the diff-in-disc design is that the outcome variables should be a smooth function across the cutoff, at least within a given bandwidth. Figure C2 shows the estimations from equation (1) but replaced the outcomes variables to a series of pre-treatment outcomes (such as income, family status, parental education, etc.). We report the coefficients as Y-standardized coefficients to better understand the magnitude of the estimates. Only 2 out of 45 estimates from the diff-in-disc model are significantly different from zero, which is likely due to chance. Most estimated magnitudes are below 0.1 standard deviation, and so quite small, which all provides evidence consistent with the quasi-experimental assumptions.

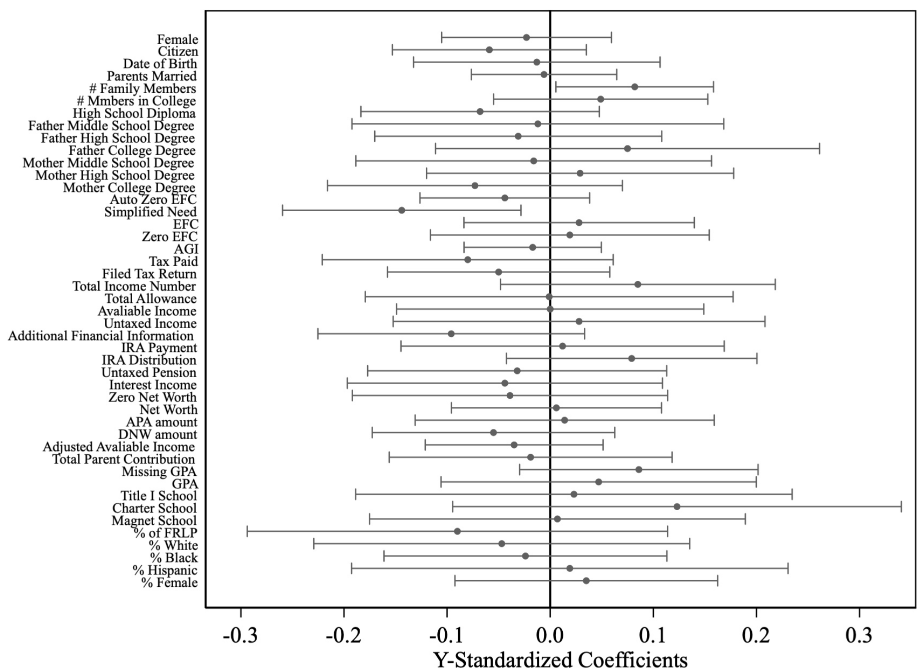


Figure C2: Placebo Test: The Estimated Discontinuity of Pre-Treatment Variables

Note: All regressions use a linear function. The samples are applicants who are first-time, dependent, Pell-eligible, and submitting within +/– 14 days from the December 15 cutoff in the 2017 and 2018 application cycle. All regressions use a local linear function and only include the day of the week as covariates.

[41] In order to formally test whether the difference in the manipulation test statistics of two application cycles is significantly different from zero, we perform a bootstrap method to resample and perform the manipulation test 1,000 times. The mean difference of the manipulation test statistics between two years is –0.134, with a standard deviation of 1.429. The p-value of the null hypothesis that the difference is not zero is 0.925.

C.3 Empirical Results

C.3.1 First-stage

Figure C3 shows the average verification rate by submission date bins in the 2018 application cycle. For people who submitted on and before December 14, approximately 90% were selected for verification, which is extremely unusual and aligns with prior news reports of elevated selection rates. However, for people who submitted on and after December 15 after the algorithm adjustment, the average verification rate discontinuously drops by a large amount that appears to be roughly 30pp. Table C1 formally estimates the discontinuity with equation (1), i.e., the diff-in-disc model. Panel A reports the basic setting using a local linear model with 14 days bandwidth and without covariates. Submitting FAFSA before the December 15 cutoff in the 2018 cycle leads to a 33pp increase in the likelihood of being selected for verification. Panel B includes FAFSA variables, GPA, and high school-by-cohort fixed effect as covariates. The results are quite similar.

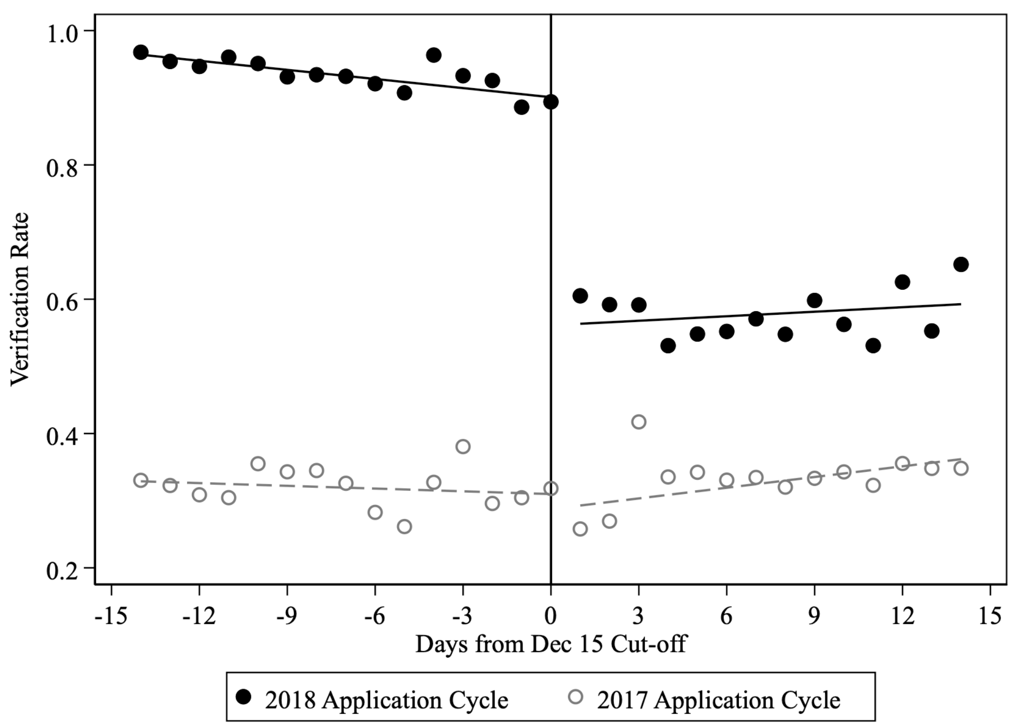


Figure C3: Verification Rate by Date of Submission

Note: Each bin stands for one day. The sample are applicants who are first-time, dependent, and Pell-eligible in the 2018 application cycle. Solid circles and solid lines stand for the 2018 application cycle. Hollow circles and dashed lines stand for the 2017 application cycle.

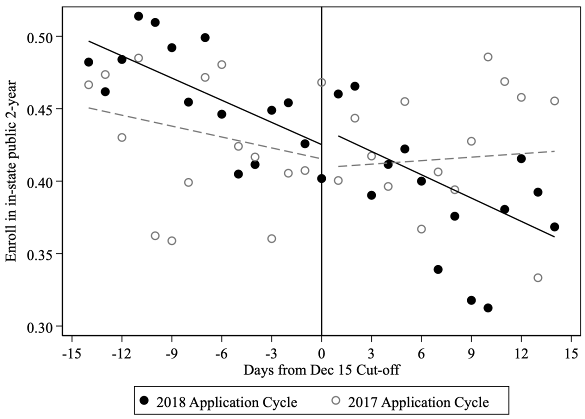
C.3.2 Impact on Enrollment

Figure C4 illustrates the relationship between enrollment outcomes and submission date. There is no graphical evidence that submission before the December 15 cutoff is associated with different enrollment rates. The second set of columns in Table C1 reports the point estimates on enrollment outcomes, with panel A using a local linear model with no covariates and panel B using a similar model with full covariates. There is no statistically significant impact on enrollment, though the estimates are noisier than our matching results. For example, point estimates across specifications show enrollment varies from a negative 4.4 to a positive 3.1pp, with all results statistically insignificant. The last columns similarly show no impact on the Cal Grant receipt, with results providing no evidence supporting the negative impact of higher verification that impacted students who submitted before December 15 in the 2018 cycle. Figure C5 in Appendix B further tests the robustness of our results by using different bandwidths. The diff-in-disc model is quite robust across different bandwidths and either linear or quadratic functions.

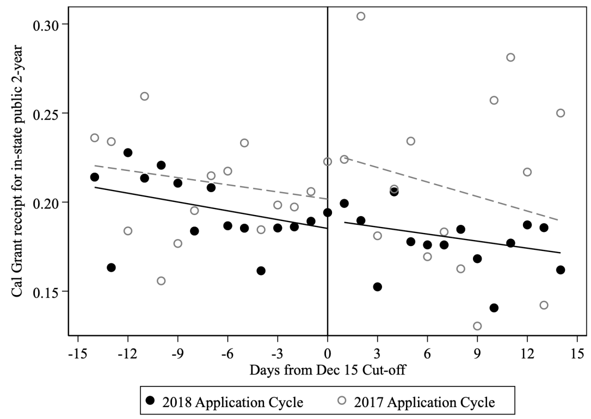
Table C1: The Effect of Getting Verification: Difference-in-Discontinuity Results

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	FAFSA	Enrollment (In-State)			Cal Grant Receipt			
	Get Verification	Public Any	Public 2-Year	Public 4-Year	Any	Public 2-Year	Public 4-Year	Private
Panel A: Basic Difference-in-Discontinuity								
$Early \times Year^{2018}$	0.330***	–0.013	–0.044	0.031	0.034	0.011	0.035	–0.014
	(0.040)	(0.025)	(0.036)	(0.029)	(0.034)	(0.031)	(0.024)	(0.012)
Panel B: with Covariates								
$Early \times Year^{2018}$	0.358***	0.002	–0.020	0.021	0.019	0.024	0.013	–0.019*
	(0.023)	(0.030)	(0.036)	(0.026)	(0.025)	(0.035)	(0.024)	(0.011)
Baseline Mean	0.577	0.754	0.398	0.356	0.556	0.180	0.331	0.046
Observations				14,821				

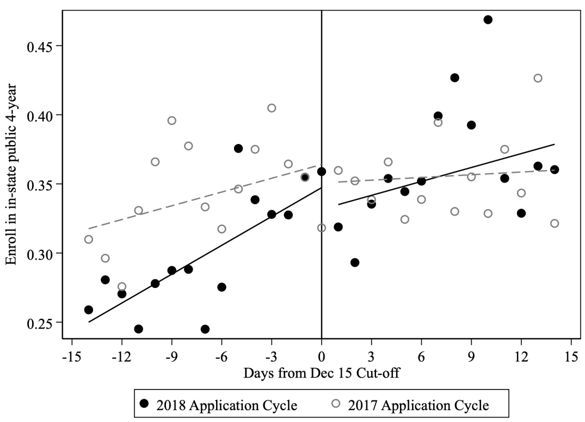
Note: Standard error cluster at submission date level in parentheses. The samples are applicants who are first-time, dependent, Pell-eligible, and submitting within +/- 14 days from the Dec 15 cutoff in the 2017 and 2018 application cycle. All regression includes the linear function of the running variable (distance of application date from Dec 15 cutoff) and day of week fixed effect. Panel B covariates include gender, citizenship status, birthdate, parental marital status, parental education level, tax filing status, number of family members, number of family members of colleges, AGI, total income number, total allowance, income tax paid, EFC, dummies indicating zero EFC, auto-zero EFC status, simplified need formula status, available income, adjusted available income, untaxable income, untaxable pension, IRA payment, interest income, net worth, APA amount, DNW amount, total contribution, high school GPA.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$



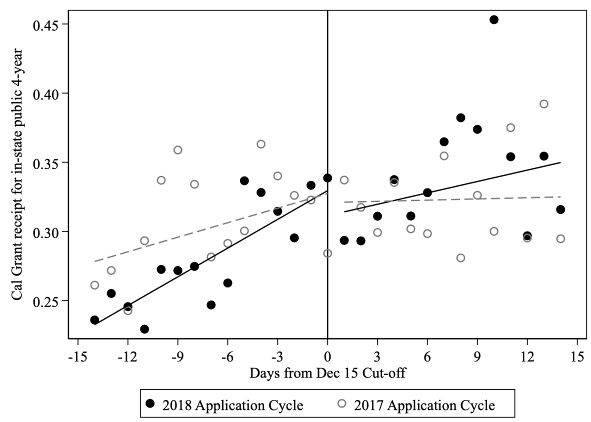
(a) Enroll in in-state 2-year public colleges



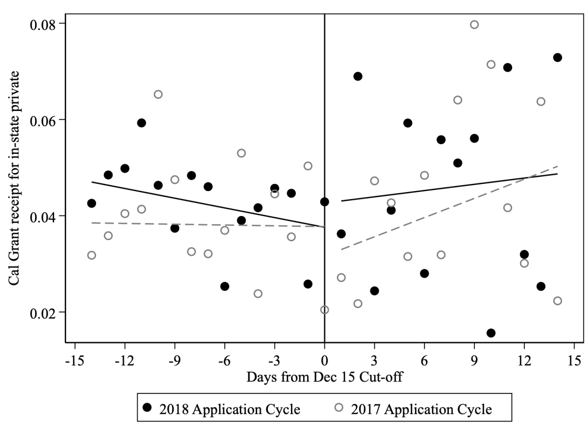
(b) Cal Grant Receipt for in-state 2-year public colleges



(c) Enroll in in-state 4-year public colleges



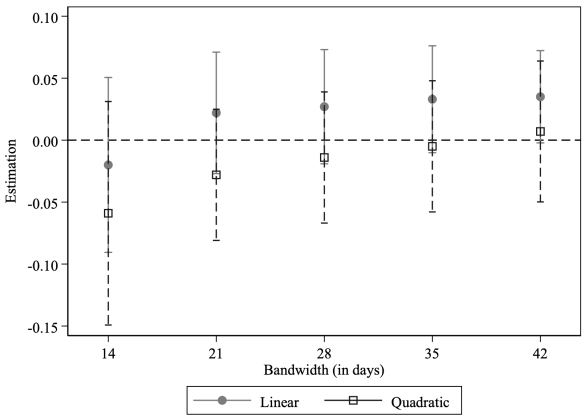
(d) Cal Grant Receipt for in-state 4-year public colleges



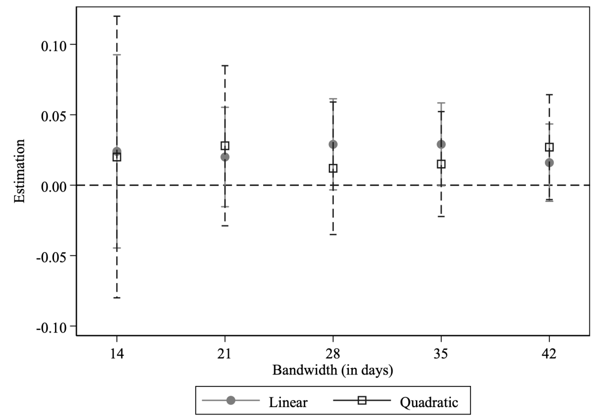
(e) Cal Grant Receipt for in-state private colleges

Figure C4: Enrollment and Cal Grant Receipt by Date of Submission

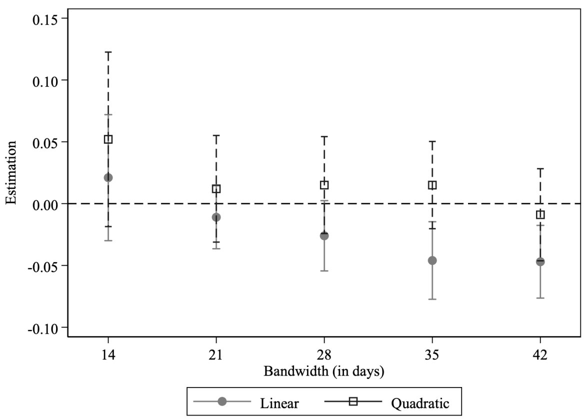
Note: Each bin stands for one day. The sample are applicants who are first-time, dependent, Pell-eligible, and submitting within +/– 14 days from the December 15 cutoff in the 2017 and 2018 application cycle. Solid circles and solid lines stand for the 2018 application cycle. Hollow circles and dashed lines stand for the 2017 application cycle.



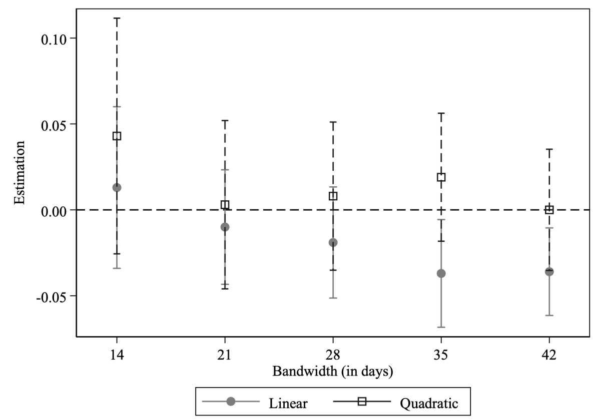
(a) Enroll in in-state 2-year public colleges



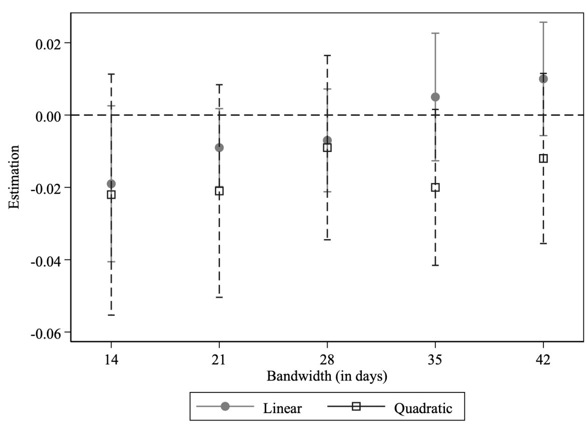
(b) Cal Grant Receipt for in-state 2-year public colleges



(c) Enroll in in-state 4-year public colleges



(d) Cal Grant Receipt for in-state 4-year public colleges



(e) Cal Grant Receipt for in-state private colleges

Figure C5: Robustness Check: Diff-in-Disc Results by Bandwidth

Note: The sample are applicants who are first-time, dependent, Pell-eligible, and submitting within +/– 14 days from the December 15 cutoff in the 2017 and 2018 application cycle. All regressions include FAFSA control and high school control. Solid circle symbols and solid line error bars stand for results from linear function estimations. Hollow square symbols with dashed line error bars stand for results from quadratic function estimations.

C.4 Discussion

We find the verification issue affected FAFSA submissions around December 15, 2017, made applicants who submitted their FAFSA form just before the weekend subject to a 33pp higher verification rate (a 57% increase over the baseline mean). However, using a diff-in-disc design, we find no evidence that this elevated verification rate negatively impacted postsecondary enrollment. The null effect on enrollment aligns with our matching results, though these diff-in-disc results are statistically noisy. The diff-in-disc design also finds no consistent evidence of the negative impact on state aid receipt, though again the confidence intervals are large and could accommodate many potential results.

The inconsistency in the findings on aid receipt could be due to the local nature of the diff-in-disc design. The diff-in-disc approach is focused on students who submit relatively early in the application cycle and may be less sensitive to verification's impacts.[42] This complier population, who would not have been normally selected in prior cycles, might be those less likely to have concerns completing the verification process.

In addition to the concern of generalizability discussed above, another limitation of our diff-in-disc approach are the significantly nosier estimates resulting from lower statistical power in this design. The standard errors from our diff-in-disc results are much higher than our matching approach, and encompass many potential results, including both our null results and potential negative impacts of verification observed in prior papers.

Despite the limitations of the diff-in-disc design, we believe this approach could complement our main results from the matching approach, and together combine to provide stronger evidence that we would if each were presented separately. Additional work that uses the same variation, but perhaps at the federal level using the national sample of FAFSA submissions, is likely better suited to estimating treatment impacts. In addition, more work to identify exogenous variation in FAFSA verification, perhaps through things like annual changes in the selection mechanism, could improve our understanding of how verification works in practice.

[42] A comparison of summary statistics shows that applicants who submit FAFSA by December are, on average, from wealthier families, with higher GPAs, and more likely to list selective colleges on their FAFSA form than those who submit after December.