Misperception and Income Response to Means-Tested Programs: Evidence from the College Financial Aid Implicit Tax

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Abstract

Means testing of college financial aid creates large implicit tax rates that affect millions of middle income families each year. These implicit tax rates can exceed 30pp, with middle income families earning between \$40k and \$140k facing the highest rates. I present the first estimates of the elasticity of parent income with respect to these taxes. I use Free Application for Federal Student Aid (FAFSA) records covering the universe of aid applicants in California from 2010-2021 and a series of difference-in-differences designs that exploit year-over-year changes in a family's effective tax rate. I estimate an elasticity of taxable income (ETI) for middle income families of 0.10. Responses are larger among families with a high share of flexible non-labor income (ETI=0.47), high assets (ETI=0.36), or higher income (\$140k to \$240k; ETI=0.28). The ETI is a sufficient statistic for the efficiency cost of a tax under the null that all individuals correctly understand the tax. However, I show based on an online survey that I conducted that many families misperceive the financial aid tax schedule. I show theoretically that when individuals misperceive a tax, the efficiency cost of the tax is affected by two channels: a bias channel measuring the average degree of misperception; and a variance channel measuring heterogeneity in misperception. A priori, misperception can increase, decrease, or have no effect on efficiency cost. The survey indicates that parents are not biased on average, but that their perceived tax rates are highly variable. Accounting for misperception, I estimate that means testing in college aid produces an efficiency cost equal to 2.3% of total aid among middle income families. Misperception increases the efficiency cost of means testing college aid by \$18.8 million per year among middle income families in California alone.

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1 Introduction

Means tested benefit programs constitute a key source of redistribution. Programs such as the EITC, SNAP, or college financial aid all target greater benefits toward lower income households. Optimal program design balances equity gains against a potential efficiency cost: means testing produces an implicit tax as a benefit is phased out, which incentivizes inefficient distortionary changes in economic behavior. The efficiency cost of a given means tested program will depend on its design. One potentially important aspect of design is how transparent or opaque the implicit incentive is: individuals can only respond to their perception of the incentive, which might not always be correct.

In this paper, I present the first estimates of the elasticity of parent income with respect to the large implicit tax in US college financial aid.[1] College financial aid is means tested against the income of a student's parents, creating a high stakes implicit tax on parent income with large marginal implicit tax rates. For each additional dollar of income a parent earns, their child's financial aid can be reduced by 30 cents or more. This dramatically reduces the incentive to earn income at the margin in the years when income affects a child's college aid. Millions of families are subject to the college aid implicit tax each year, with the highest marginal implicit tax rates concentrated among middle income families earning between \$40k and \$140k. In order to fully assess the equity-efficiency tradeoff inherent in means tested college aid, one must measure the elasticity of parent income, which governs the efficiency cost. However, to my knowledge there exist no estimates of this key elasticity. One likely reason for this is the limited and restricted nature of data sources available to study this question. The ideal data source links college-attending children with information on their parents' income and other aid inputs that determine a family's marginal implicit tax from aid in a panel setting and has many observations. Few existing datasets meet these criteria, and those that do are restricted-access administrative data.

I draw on the universe of Free Application for Federal Student Aid (FAFSA) records in California from 2010 through 2021 to estimate the elasticity of taxable income (ETI) with respect to the implicit tax on parent income due to college aid among middle income (\$40k to \$140k) and high income (\$140k to \$240k) families. I estimate the ETI for middle income families using a difference-in-differences design around the first year of income that families expect will determine college aid. My difference-in-differences design compares the change in income in a given pair of years across two types of families: the first (treated) expect that only income in the second year will affect their financial aid, so they are becoming newly exposed to the incentive to reduce income; the second (control) know that income in both years will affect their aid, so they face no change in incentives. I estimate this difference-in-differences specification among middle income families who face the highest marginal implicit tax rates

[1] Several earlier papers (e.g., Feldstein, 1995; Long, 2004; Monks, 2004) have studied impacts on savings, and two recent papers (Darolia, 2017; Park and Scott-Clayton, 2018) have studied impacts on students' own labor supply.

from college aid.

I complement this analysis with a second difference-in-differences design that exploits changes in implicit taxes on a different margin. The aid schedule depends on the number of children in college. This creates changes in effective tax rates when a family's second child starts college. I use this to obtain a second estimate of the ETI, this time for higher income families who face the largest changes in their effective tax rate when a second child enrolls. I compare families who enroll their first child in the same year but vary in the spacing of their children.

I estimate an ETI for middle income families of 0.10, meaning that a 10% increase in the marginal implicit tax rate from college aid would produce a 1.0% reduction of income on average. I find that the elasticity is substantially higher among families who have a high share of income accounted for by flexible non-labor sources (ETI = 0.47) or who have high assets (ETI = 0.36). My second design, based on high income families, yields an estimated ETI of 0.28. Point estimates of the ETI for high income families are also larger among families with a high share of income accounted for by flexible non-labor sources or with high assets, but these subgroup estimates are very noisy due to smaller sample sizes in the high income range. My estimates are consistent with reduced form estimates of the response of parent income to the implicit tax in college aid in a separate project by Gebbia et al. (2023), wherein we use federal income tax data and an event study design around the first year a parent's income is used to determine a child's college aid, suggesting pre-trends or selective financial aid application filing are not important confounders.

Because college aid is temporary and its timing can be anticipated, my estimates of the ETI can also be viewed as estimates of the Frisch elasticity that governs intertemporal income decisions. Micro estimates of the Frisch elasticity therefore serve as relevant benchmarks for comparison. The closest papers in this spirit are those that exploit "tax holidays" – instances in which income was temporarily not subject to an income tax as a country transitioned its income tax system – to estimate the Frisch elasticity, where the college aid setting can be seen as an "anti tax holiday" that temporarily increases the marginal tax rate on income. Martínez et al. (2021) estimate the Frisch elasticity of labor income in an event study design that exploits geographic differences in timing of a tax holiday in Switzerland, estimating an elasticity of 0.025 overall and 0.25 among the self-employed. Similarly, Tortarolo et al. (2020) use a regression discontinuity design to study a tax holiday in Argentina that only applied for workers with past income below a specified threshold, finding an elasticity of labor income of 0.017. My estimates of the ETI for middle and high income groups of 0.10 and 0.28, respectively, are somewhat higher than these. However, my measure of income – which is the measure of income used to determine financial aid – includes non-labor sources in addition to labor income, which likely contributes to the discrepancy as non-labor income appears more responsive.

An important aspect of the college financial aid system is that it is complex and opaque. College aid formulas are highly nonlinear over parent income, including interactions with other aid inputs like assets or family size. This suggests that families may not have perfect awareness of the tax rates that they face. An existing literature highlights the significant impact of uncertainty over and misperception of the level of aid a student would receive on academic outcomes like application and enrollment (Bettinger et al., 2012; Hoxby and Turner, 2015; Dynarski et al., 2021). A recent book argues that the complexity and opacity of college aid is a serious issue for higher education, and that existing tools do not make it simple for families to understand the level of aid they can expect to receive (Levine, 2022). If families do not know the level of aid they can expect, it is even less likely that they know the marginal reduction of aid they would incur due to a marginal increase of income.

I develop a model of income choice in the presence of a tax that individuals can misperceive, and I derive an expression for the impact of misperception on the deadweight loss (DWL) that results from the tax. Misperception affects DWL through two channels: a bias channel, reflecting the average level of misperception; and a variance channel, reflecting heterogeneity in misperceptions across individuals. Average misperception affects DWL because this determines the average income response to the tax. Variance of misperception affects DWL because DWL generally increases with the square of the tax rate. A priori, misperception can increase, decrease, or have no effect on DWL. For example, if the average perceived tax rate is lower than the true tax rate and the variance of perceptions is sufficiently low, misperception can decrease DWL. Alternatively, if either (i) the average perceived tax rate is greater than the true tax rate or (ii) the average perceived tax rate is equal to or less than the true tax rate and the variance of perceptions is sufficiently large, then misperception can increase DWL.

I administer an online survey to 3,158 parents of children age 25 and younger to directly measure perceived college aid tax rates. I use these perceived rates in combination with the reduced form ETI's from my difference-in-difference analyses to compute the structural elasticity of income with respect to the perceived tax rate as well as the impact of misperception on DWL. Despite the complexity of college aid, the survey indicates that parents' perception of their marginal implicit tax rate from aid is close to the truth on average. As a result, the structural ETI with respect to the perceived marginal implicit tax rate only differs from the reduced form elasticity with respect to the actual rate by 10%. However, the variance of misperception is large, reflecting substantial heterogeneity in misperception across individuals. Accounting for misperception, I estimate the efficiency cost of means testing in college aid to equal 2.3% of total aid. Misperception increases the efficiency cost of means testing by $18.8 million per year among middle income families in California alone. The variance channel accounts for effectively all of the increase in DWL from misperception. This result is consistent with Taubinsky and Rees-Jones (2018), who find that heterogeneity in individual salience of a sales tax increases the efficiency cost of the tax by over 200%.

My analysis provides some of the first direct evidence on whether improving transparency of transfer programs would raise or lower welfare, and the results run counter to the long-standing dominant intuition. A common previous result has been that individuals tend to underestimate their marginal tax rate in progressive tax systems, often replacing the marginal rate with the average rate, which in turn reduces distortionary changes to income and thereby increases welfare (de Bartolome, 1995; Liebman and Zeckhauser, 2004; Ito, 2014; Taubinsky and Rees-Jones, 2020). In the context of college financial aid, I do not find that parents systematically underestimate their marginal tax rate, but instead that perceived rates are close to true rates on average. Previous papers studying the impact of tax misperception on welfare do not account for the role of heterogeneous misperceptions. I find that misperception of tax rates in college aid is highly variable, and that this variability doubles the DWL from means testing. Counter to the conventional view, my results indicate that misperception of the implicit tax schedule in college aid substantially increases the efficiency cost of means testing, rather than decreasing it. My results highlight the central importance of accounting for the variance of misperceptions. The methods in this paper can be applied in various other settings with complex price or tax schedules to study whether improving transparency would raise or lower welfare.

This paper builds primarily on three literatures. First is the literature on implicit incentives in college financial aid. It has been observed for decades that college aid is structured as an implicit tax on income and savings (Case and McPherson, 1986; Edlin, 1993; Dick and Edlin, 1997). Several early papers focused on the elasticity of savings with respect to college aid incentives (Feldstein, 1995; Long, 2004; Monks, 2004). Two recent papers have studied whether students change their labor supply during college in response to similar aid incentives placed on student income (Darolia, 2017; Park and Scott-Clayton, 2018).

To my knowledge, this paper provides the first estimates of the elasticity of parent income with respect to the college aid implicit tax. Parent income explains the majority of variation in college aid. The elasticity of parent income is therefore a necessary input to evaluate the equity-efficiency tradeoff inherent in means tested college aid and to build upon existing assessments of the optimal aid schedule (Colas et al., 2021).

The second literature this paper builds on is the long literature studying the response of labor supply and income to explicit or implicit taxes (Mirrlees, 1971; Ashenfelter and Plant, 1990; Feldstein, 1995; Auerbach et al., 2000; Goolsbee, 2000; Gruber and Saez, 2002; Eissa and Hoynes, 2006; Chetty et al., 2013). Much of this literature focuses on either very low income families (e.g. responses to social programs like the Earned Income Tax Credit (EITC)) or very high income families (e.g. executive compensation tax), with few studies focusing specifically on the responsiveness of middle income families. Marginal implicit tax rates from college aid are highest among middle income families earning between \$40k and \$140k. As a result, my main analysis produces one of few estimates of the elasticity of taxable income specifically for this middle income range.

The third literature this paper builds on is the growing literature studying the impact of information frictions on changes in behavior in response to explicit or implicit taxes. Public economists are concerned with substitution responses to explicit or implicit taxes because substitution effects determine efficiency cost, for which the elasticity of taxable income (ETI) is frequently a sufficient statistic (Feldstein, 1995; Feldstein, 1999; Gruber and Saez, 2002). Behavior changes due to a tax depend not only on the incentives the tax actually creates, but also on the extent to which the population subject to the tax fully understands and accounts for those incentives when making decisions. Survey evidence directly measuring perceptions of taxes finds that individuals often misperceive their marginal tax rate, particularly in the context of a nonlinear tax schedule (Fujii and Hawley, 1988; Rees-Jones and Taubinsky, 2020). Reduced form evidence finds patterns consistent with misperception of tax rates impacting behavior in various settings with nonlinear tax schedules (de Bartolome, 1995; Liebman and Zeckhauser, 2004; Chetty et al., 2013; Chetty and Saez, 2013; Ito, 2014; Liebman and Luttmer, 2015; Feldman et al. 2016; Kostøl and Myhre, 2021), including experimental evidence that complexity of the tax system directly contributes to underreaction to taxes (Abeler and Jäger, 2015). The extent to which information frictions shape empirical elasticities is directly relevant to optimal tax policy (Goldin, 2015; Rees-Jones and Taubinsky, 2018; Farhi and Gabaix, 2020; Craig and Slemrod, 2023).

I make three contributions to the literature on information frictions and taxable income elasticities. First, to my knowledge, this is the only paper to combine reduced form elasticity estimates with direct measures of tax perceptions in the context of a nonlinear tax schedule.[2] Combining reduced form elasticity estimates with direct measures of perceptions allows me to estimate the structural elasticity of income with respect to the perceived tax, which is the elasticity that is relevant to welfare. Second, I study the role of information frictions in a setting with a unique combination of factors that makes the implicit tax schedule especially opaque: the college aid implicit tax schedule is highly nonlinear, including nonlinearities over income conditional on other inputs along with interactions between income and other factors (assets, number of children enrolled, parent age, etc.) that shift the entire schedule; existing information sources are often limited, and it is not always straightforward to determine one's marginal implicit tax rate from college aid. Third, my results highlight the central role of the variance of misperception in affecting the efficiency cost of a complex or opaque tax. This finding builds on two

[2] Notable exceptions that combine reduced form elasticities with survey measures of perceptions are Chetty et al. (2009) and Finkelstein (2009). Each of these papers, however, studies linear tax systems: Chetty et al. (2009) study a sales tax on grocery store items and the excise tax on alcohol; Finkelstein (2009) studies a road toll. Consequently, these papers are focused on incomplete salience of taxes as opposed to misperception, which is especially relevant in nonlinear settings.

recent results that emphasize the impact of heterogeneity in salience of a sales tax on the efficiency cost of the tax (Rees-Jones and Taubinsky, 2018; Morrison and Taubinsky, 2023), but to my knowledge this is the first paper to empirically consider the impact of heterogeneity in misperceptions on the efficiency cost of a tax, which is significant in the college aid setting.

The rest of the paper proceeds as follows. Section 2 characterizes the implicit tax structure in college aid. Section 3 outlines a model consistent with the data, which accounts for misperception of a temporary implicit tax schedule in a dynamic income problem. Section 4 describes the data. Section 5 presents the empirical methodology and estimates of reduced form elasticities. Section 6 reports results that combine reduced form elasticity estimates with the online survey data, including estimates of the structural elasticity, deadweight loss with and without misperception, and the contributions of the bias and variance channels of misperception to deadweight loss. Section 7 includes a discussion of the findings and their relevance to policy. Section 8 concludes.

2 Background: Implicit Taxes in College Financial Aid

2.1 College Aid Creates a Temporary, High-stakes Incentive for Middle Income Families to Reduce Income

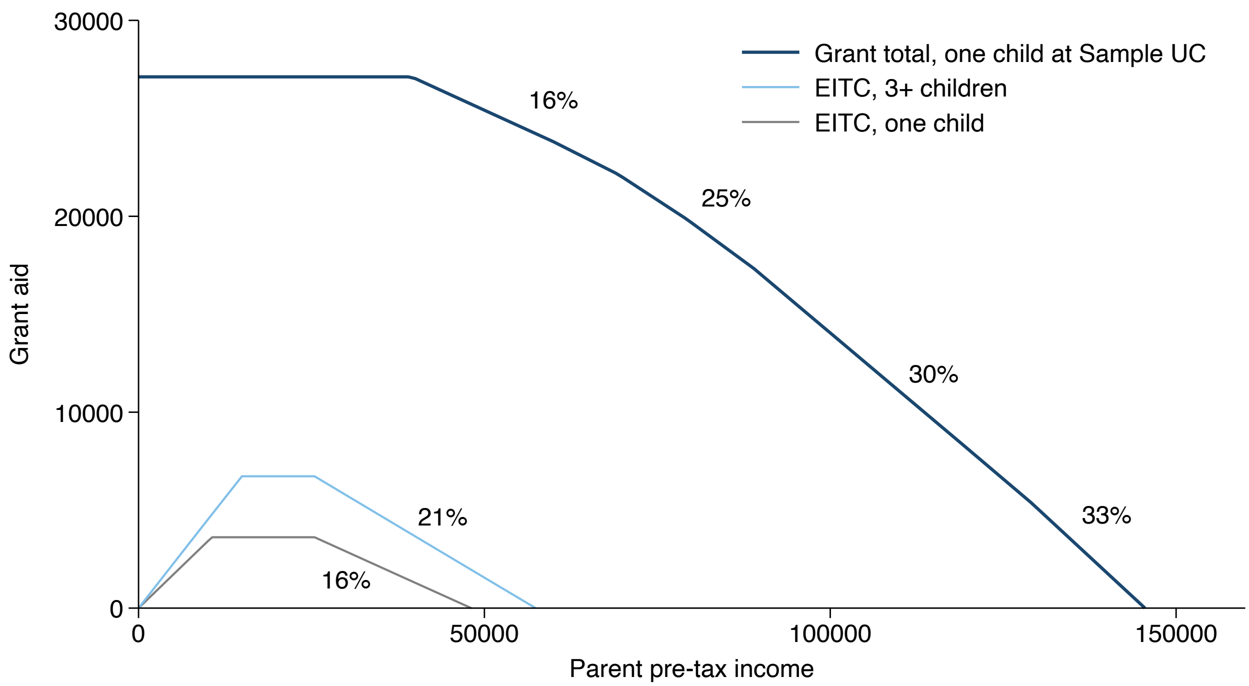
Most students who attend a four-year college in the US do not pay the full "sticker cost". A college's sticker cost is the published annual cost to attend that college, which includes tuition and fees, housing, and other important costs like books, supplies, and transportation. Most students receive financial aid that lowers the effective cost they pay. Financial aid comprises grants or scholarships – money that covers college costs and does not need to be paid back – along with loans that are typically offered on favorable terms. Financial aid is available to students through sources including the federal government, state governments, individual colleges, and private entities. In the remainder of this paper, I will use the terms "financial aid" and "aid" to refer only to grants and scholarships offered by the federal government, state governments, and individual colleges, as this is the component that creates high-stakes incentives over income earned by the parents of college students.

The financial aid a student receives is heavily means-tested against the income of their parents, so that two students with parents earning different incomes can pay vastly different net costs to attend the same college. Figure 1 displays the total grant aid a student can expect to receive at a sample University of California (UC) campus for one year of enrollment based on their parents' pre-tax income. The information in Figure 1 is based on the Net Price Calculator (NPC) page on the sample UC's financial aid website.[3] The annual total cost of attendance – including tuition and fees, housing, and

[3] All colleges in the US that participate in Title IV financial aid programs – allowing their students to access federal grants, federal student loans, and federal work-study to assist in paying for college – are required to host a NPC website that allows students to enter several aspects of their family background and receive a tailored estimate of the financial aid they will receive and the net cost they will pay. As discussed in Section 2.4, however, information on the broader

other expenses – is approximately $37k. According to the sample UC's NPC website, students whose parent pre-tax income is below $40k can expect to receive approximately $27k in grants per year, cutting their annual cost of attendance down to $10k. (Students are expected to cover the remaining cost through so-called "self help" - summer and term-time earnings and student loans.) Beginning at incomes slightly above $40k, aid is gradually phased out until it reaches zero for students whose parent income is above $140k, in which case the family's annual net cost is equal to the full sticker cost of $37k.

Figure 1: Example Grant Aid Schedule at Sample UC vs. EITC



Notes: The top line in the figure shows the expected annual grant aid for one child enrolled at the Sample UC based on parent pre-tax income. The middle line is the EITC schedule for a family with 3+ children, and the bottom line is the EITC schedule for a family with one child. Marginal implicit tax rates are labeled in the figure.

Means-testing of financial aid over parent income creates a strong incentive for middle income families with a child in college to reduce reported income. In the case of the sample UC, families with incomes between $40k and $140k, each additional dollar of reported income reduces the financial aid award (and thus increases the family's net cost) by 16 to 33 cents. This phaseout of aid is akin to implicitly taxing income at the margin during each year of income reported on a student's FAFSA, with marginal implicit tax rates ranging from 16% to 33%. The marginal implicit tax from college financial aid adds

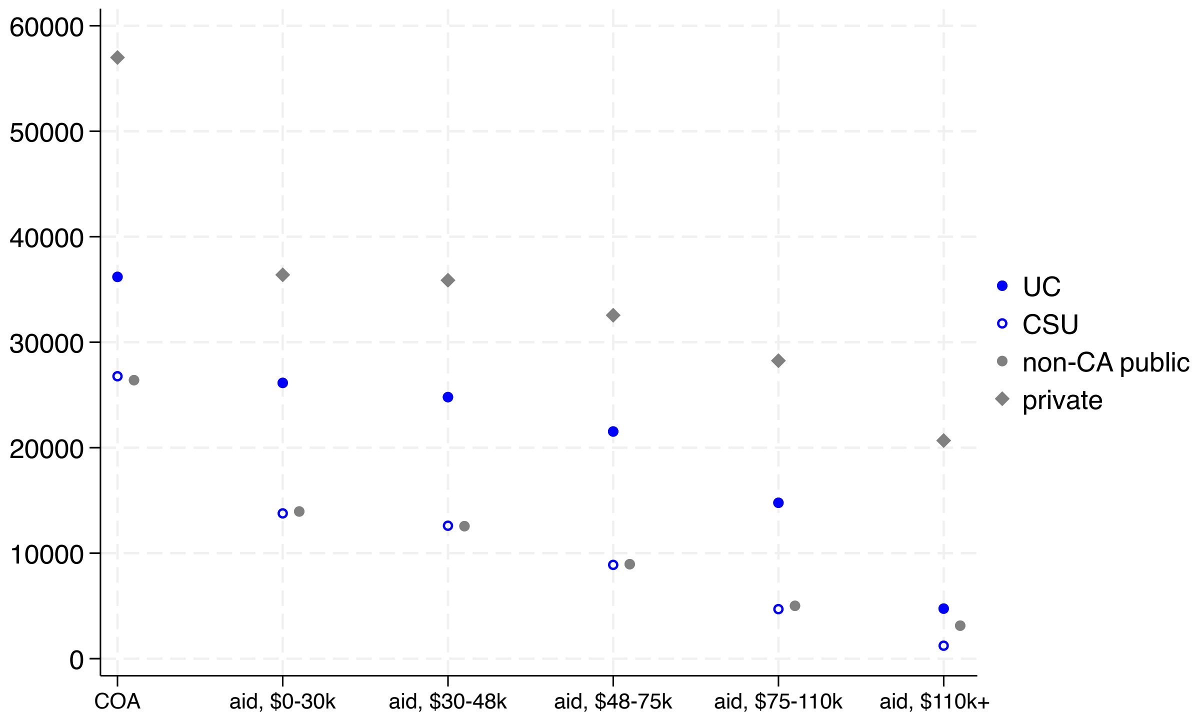
aid schedule over income like that shown in Figure 1 can only be obtained by repeatedly entering different inputs to the NPC and recording the various aid estimates. Additionally, as discussed in Section 2.4, college aid varies not only with income but also with family savings, family structure, and other family characteristics. The information in Figure 1 was produced by holding these other inputs fixed.

on top of other marginal incentives a family faces on their income such as federal and state income taxes, so that middle income families with a child in college can face an all-in marginal tax on income exceeding 50%, with some cases even exceeding 60%.

The implicit tax on income from college aid is large relative to other means-tested programs in terms of both the magnitude of marginal implicit tax rates and the wide range of income levels subject to them. For comparison, Figure 1 also shows the schedules of the Earned Income Tax Credit (EITC) for a family with one child and for a family with three or more children, which is the most generous EITC schedule. The EITC phases out at a marginal implicit tax rate of 16% for a family with one child and at 21% for a family with three or more children. Phaseout of the EITC begins at incomes just below $30k and extends up to approximately $50k for a family with one child and $60k for a family with three or more children. In comparison, the phaseout region of college aid at the sample UC campus applies similar and even larger marginal implicit tax rates to a range of income that is roughly three times as wide as that affected by EITC phaseout, with college aid phaseout also affecting more middle income than low income families. While the impact of the phase in and phaseout regions of the EITC on labor supply and income has been the subject of a long literature (see e.g. Eissa and Hoynes, 2006; Chetty et al., 2013), there are currently no estimates of the response of middle-income parents' labor supply or income to the implicit tax in college financial aid.

The large implicit tax in college aid applies to income earned by millions of families across the US every year. Figure 2 puts the previous UC aid schedule in the national context using publicly available data reported annually through the US Department of Education's (ED) Integrated Postsecondary Education Data System (IPEDS), which is sourced from reports that colleges issue to the ED. The figure reports the average sticker cost of attendance (COA) for a student living on campus alongside average grant and scholarship aid awarded to families with income in five bins: $0-30k, $30-48k, $48-75k, $75-110k, and above $110k. These statistics are shown separately as averages among the nine UC campuses serving undergraduates, 23 California State University (CSU) campuses, all public four-year colleges outside California, and all private four-year colleges nationwide. Similar to the UC schedule above, aid begins to phase out beginning at incomes generally above $48k, with the phaseout affecting a wide range of middle income levels at high marginal implicit tax rates. Consider the difference in average aid for families with income from $48-75k compared to those with income from $30-48k. As a rough estimate of the marginal implicit tax rate from aid over this range, we can scale the difference in aid across the two income bins by the median income level of each bin. This produces a marginal implicit tax rate of 14% at UC's, 17% at CSU's, 16% at public four-year colleges outside California, and 15% at private four-year colleges. Moving from the $48-75k range to the $75-110k range produces marginal implicit tax rates of 22% at UC's, 14% at CSU's, 13% at public four-year colleges outside California, and 14% at private four-year colleges. Phaseout rates at UC's are generally high relative to other colleges, but the implicit tax on parent income is a consistent feature of financial aid at four-year colleges across the country, with average rates nationwide still being considerable and affecting a wide range of middle income families. To the extent that merit-based scholarships are positively correlated with family income, these measures of the marginal implicit tax rate from aid based on IPEDS data will understate the true degree of phaseout over income.

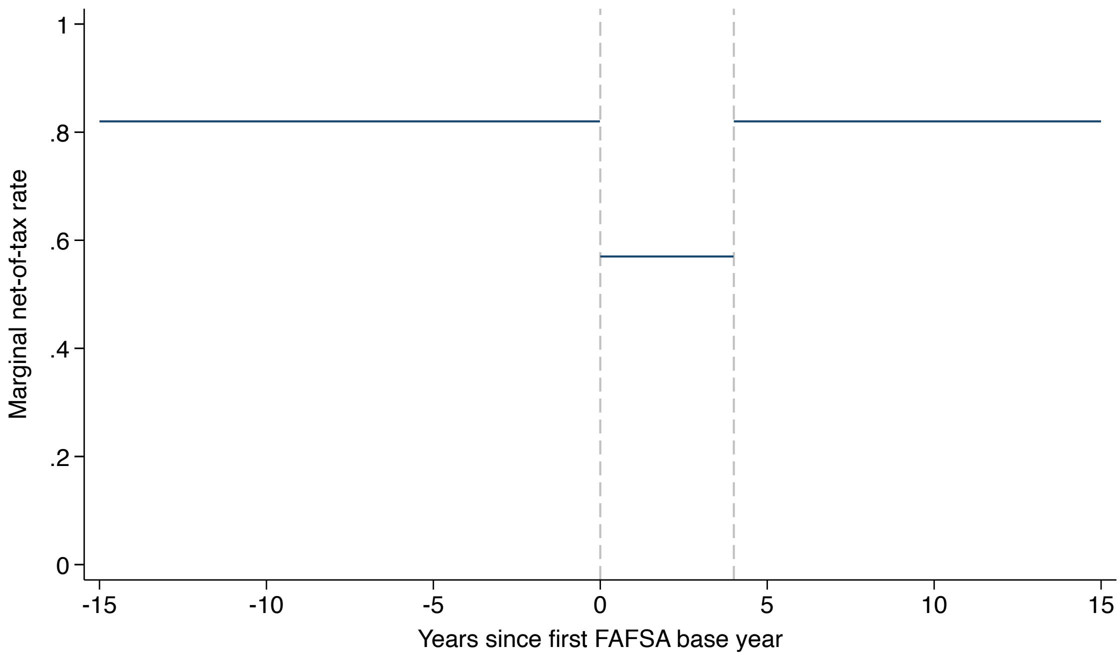
Figure 2: Aid Schedule across Four-year Colleges



Notes: The figure uses IPEDS data to plot annual total cost of attendance and average grant and scholarship aid in each of five income bins, separately among University of California (UC), California State University (CSU), non-CA public, and private four-year colleges.

The college aid implicit tax on income is of course temporary, as it only affects income earned in the years that are used to determine financial aid. As a result, the setting is similar to studies of "tax holidays", wherein income was temporarily not subject to any income tax as several countries transitioned the timing of their income tax systems (Tortarolo et al., 2020; Martínez et al., 2021). These studies leverage the temporary nature of the tax holidays to credibly estimate the Frisch elasticity of labor supply and income, which determines the intertemporal substitution response of income to a temporary and anticipated change in the effective wage rate. The college aid setting creates an "anti-tax holiday", wherein income is temporarily subject to a higher marginal tax rate, so the net-of-tax rate is temporarily lower. Figure 3 displays the anti- tax holiday nature of the college aid implicit tax, emphasizing its temporary nature. Figure 3 shows the marginal net-of-tax rate on income for an $80k earner with a child who attends the sample UC for four years. In the years before and after college, the marginal net-of-tax rate for this parent is just over 80%, meaning they keep just over 80 cents out of the marginal dollar of income. This rate accounts for federal and state income taxes. In the four years when income is used to determine college aid, the net-of-tax rate drops to just under 60%, meaning the parent keeps just under 60 cents out of the marginal dollar of income, with over 20 cents now being lost in the form of reduced financial aid. Due to the temporary nature of the college aid implicit tax, the relevant elasticity that determines income changes in years that affect aid is the Frisch elasticity. As a result, the estimates in this paper provide an additional source of micro estimates of the Frisch elasticity of income.

Figure 3: Marginal Net-of-tax Rate for $80k Earner around College



Notes: The figure plots the marginal net-of-tax rate on income faced by a parent earning $80k around the years in which parent income is used to determine financial aid for the child. The marginal net-of-tax rate accounts for federal and state income taxes along with the implicit tax from college aid.

In sum, college financial aid creates a large implicit tax on parent income in the years when income is used to determine a child's financial aid, which applies to a wide range of primarily middle income families. This implicit tax is found at four-year colleges across the US. Because the college aid implicit tax is temporary, the Frisch elasticity of intertemporal substitution governs the response of income to aid incentives, which is weakly larger than the Hicksian or Marshallian elasticities due to the ability to shift income producing behavior across years. Taken together, these characteristics of college aid in the US create the potential for large deadweight loss if parents of college-going children reduce income in the years when income affects their child's aid. However, there are currently no estimates of the elasticity of parent income with respect to the college aid implicit tax, which is the key parameter that determines efficiency costs.

2.2 How Students Apply for Financial Aid

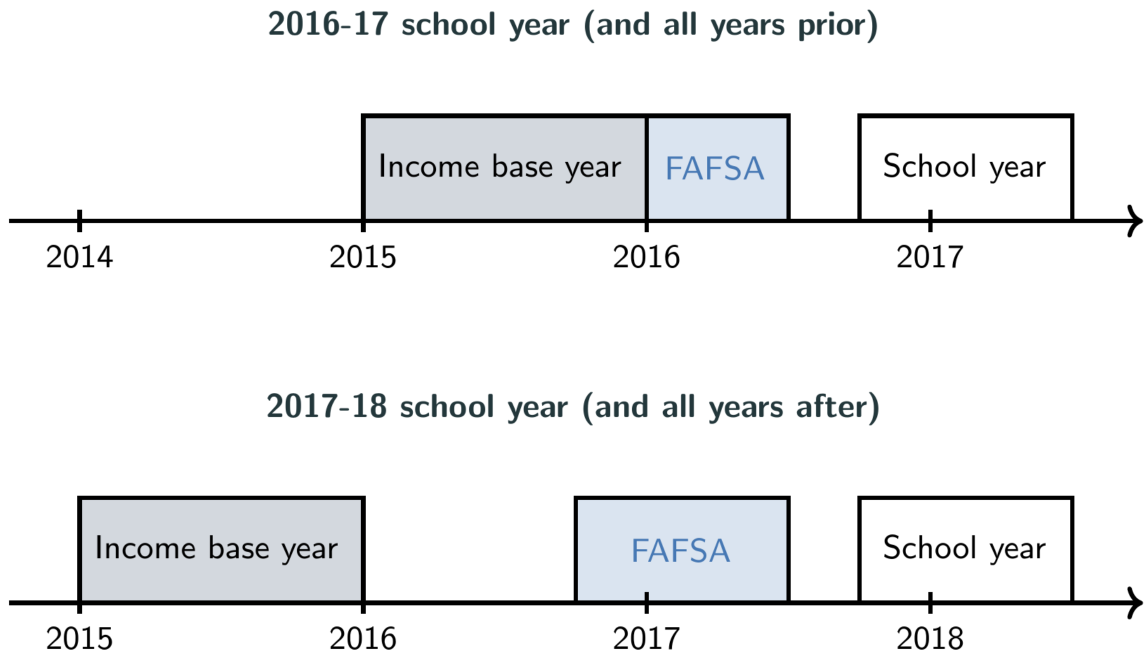
Students apply for financial aid using a uniform federal application form called the Free Application for Federal Student Aid (FAFSA). While the FAFSA is a federal form, it is also shared with states and colleges, so that ultimately the information a student records on their FAFSA will be used to determine their financial aid from federal, state, and institutional (i.e. individual colleges) sources. The FAFSA records a vast amount of information about the student and their family, including information regarding parent and student income and assets, family structure, residence, and more.[4] Students applying for financial aid are required to re-file a new FAFSA corresponding to each year of enrollment. The information recorded on FAFSA's is audited by the Department of Education (ED) at rates much higher than, for example, federal income tax returns. Historically, 30% of FAFSA applications were audited; recently, the percentage has been reduced to 18% (Hoover, 2020). Lower-income students who are eligible for the federal Pell grant are audited at a much higher rate (Guzman-Alvarez and Page, 2021)

Figure 4 shows the financial aid application timeline. The first panel of Figure 4 shows the timeline that applied in the 2016-17 school year and all years prior. The school year begins in the fall, typically in August or September. A student applying for aid would fill out the FAFSA anywhere from January 1 to approximately May in the same year of enrollment, for example a student would fill out a FAFSA for the 2016-17 school year starting in January of 2016. The income referenced on the FAFSA would come from one year prior, for example a student would report information on family income earned in 2015 to determine financial aid for the 2016-17 school year. Beginning with the 2017-18 school year and applying to all years thereafter, the base year of income was shifted back by one relative to the school year. For example, aid for the 2017-18 school year was also based on income earned in 2015. This change of the base year was due to a policy shift known as "prior-prior". The policy shift was intended to allow students to submit their FAFSA earlier, now beginning in October of the year before

[4] For many students the aid award is based solely on the information on the FAFSA. Two exceptions are worth noting. First, a smaller set of primarily private colleges supplement the information on the FAFSA using a form called the CSS Profile. These colleges represent a small share of nationwide college enrollment, and an even smaller share of the sample of students in California used in this paper. Second, states and colleges often offer merit scholarships based on information (like the high school GPA) that is not recorded on the FAFSA. For example, California's Cal Grant program offers scholarships to California students meeting minimum high school GPA requirements who attend a California college. Cal Grants cover as much as full tuition and fees at a UC campus, approximately $13k. However, it is not clear that Cal Grant significantly impacts the marginal implicit tax rate a student faces on their total aid package, as it often simply offsets other aid. As an example, see Figure 19 in Appendix C, which shows the UC Education Financing Model (EFM), which reflects the UC system's intended aid schedule over income for UC students. The figure makes clear that there are multiple sources of aid a student can receive, and even with Cal Grant they face the same overall phaseout schedule.

enrollment, so that students would have more time to assess financial aid packages. The shift also made it easier for families to use the IRS Data Retrieval Tool, which automatically fills in FAFSA income information from federal income tax returns.

Figure 4: Financial Aid Application Timeline



Notes: The figure shows the relative timing of the income base year, the FAFSA filing window, and the relevant school year. The top panel shows the financial aid application timeline for academic year 2016-17 and all years prior. The bottom panel shows the timeline for academid year 2017-18 and all years after.

2.3 How Financial Aid is Determined

At many colleges across the US, financial aid is determined in large part by the federal formula known as Expected Family Contribution (EFC). EFC is a measure of the annual amount a student and/or their family is expected to pay for college. The amount is increasing in income and assets of both the parents and the student, with parent income explaining most of the variation in EFC. EFC determines eligibility for federal Pell grant assistance and the amount a student will receive. Additionally, most colleges use EFC as an important input to their financial aid awards, tying aid roughly to "Need", which is the gap between the total annual cost of attendance and a student's EFC. For example, the aid estimates reported on the financial aid website of the sample UC described in Figure 1 are exactly equal to the difference between COA and EFC, which is equal to Need.

2.4 The Implicit Tax in College Aid is Complex and Difficult to Learn

College financial aid is remarkably complex. The EFC formula, which underlies much of aid determination, is highly nonlinear. The aid schedule at the sample UC in Figure 1 holds fixed all inputs aside from parent income such as assets, number of children in college, student income, and more. The full EFC formula incorporates interactions across these various inputs, so that even the nonlinearity of aid over parent income shown in Figure 1 will vary with other inputs. On top of this, the EFC formula also includes several kinks and notches, each of which varies by characteristics like parent age or number of people in the household and often changes from one year to the next.[5] Figure 5 shows a brief excerpt from the 2021 EFC formula, reflecting the various inputs, allowance amounts calculated from tables not shown in the figure, conversion rates, and more that ultimately determine EFC and aid. As a result of the significant degree of complexity in aid formulas, it is exceedingly difficult for an individual student or their family to determine precisely the marginal implicit tax they face on parent income or any other determinant of aid.

Compounding the complexity of financial aid, information sources like news outlets do not make it straightforward for a family to learn the marginal implicit tax rate they should expect to face. Figure 6 shows excerpts from two online news articles describing how families can maximize their financial aid. Both excerpts make it clear to understand that there is an incentive to temporarily reduce income with section headers reading "Postpone parental income" and "Minimize income in the base year." However, rather than list the marginal implicit tax rates that families in different income ranges might face, the first piece instead describes the average tax rate (in this context, the percent of income a family is expected to pay toward college, but not at the margin), while the second piece only lists what is roughly the maximum marginal implicit tax rate of 30%.

How can families learn the implicit marginal tax rate they should expect to face from college aid? Likely the two best options are to (1) learn the EFC formula and evaluate it at multiple points of parent income with other inputs fixed, or (2) use a college's Net Price Calculator (NPC) website, plugging in different values of income and checking how predicted aid changes. The sample UC aid schedule in Figure 1 comes from method (2). Colleges do not tend to post images or information directly conveying the content of the aid schedule over income as in Figure 1 on their financial aid websites. Instead, families must be savvy enough to go to a college's NPC website, enter one set of

[5] For example, parent income below the Income Protection Allowance (IPA) does not affect EFC, and the IPA varies both by the number of college students in the household and the total number in the household. Parent assets below the Education Savings and Asset Protection Allowance are similarly excluded from the EFC, and this amount varies by the number of parents in the household and the age of the older parent. Families with total parent income below a threshold of approximately $25k – the threshold changes slightly each year – who also meet an additional set of criteria qualify for an automatic zero EFC, creating a notch. Families with total parent income below $50k who also meet an additional set of criteria qualify for the Simplied Needs Test (SNT) and do not need to report any information on assets, creating a notch whereby these families escape the asset tax component of aid calculations altogether.

Figure 5: Excerpt of 2021 Expected Family Contribution (EFC) Formula

Total parents' income earned from work	=	
3. Taxable income (If tax filers, enter the amount from line 1 above. If non-tax filers, enter the amount from line 2.)*		
4. Total untaxed income and benefits: (total of FAFSA/SAR #92a through 92h)	+	
5. Taxable and untaxed income (sum of line 3 and line 4)	=	
6. Total additional financial information (total of FAFSA/SAR #91a through 91f)	−	
7. TOTAL INCOME (line 5 minus line 6) May be a negative number.	=	

ALLOWANCES AGAINST PARENTS' INCOME		
8. 2019 U.S. income tax paid (FAFSA/SAR #85) (tax filers only) If negative, enter zero.		
9. State and other tax allowance (Table 1) If negative, enter zero.	+	
10. Parent 1 (father/mother/stepparent) Social Security tax allowance (Table 3)	+	
11. Parent 2 (father/mother/stepparent) Social Security tax allowance (Table 3)	+	
12. Income protection allowance (Table 4)	+	
13. Employment expense allowance: • Two working parents (Parents' Marital Status is "married" or "unmarried and both parents living together"): 35% of the lesser of the earned incomes, or $4,000, whichever is less • One-parent families: 35% of earned income, or $4,000, whichever is less • Two-parent families, one working parent: enter zero	+	
14. TOTAL ALLOWANCES	=	

*STOP HERE (at line 3) if the following are true:

Line 3 is $27,000 or less **and**

- The parents did not file a Schedule 1 with their IRS Form 1040 or they are not required to file any income tax return **or**

PARENTS' CONTRIBUTION FROM ASSETS		
16. Cash, savings, and checking (FAFSA/SAR #88)		
17. Net worth of investments** (FAFSA/SAR #89) If negative, enter zero.	+	
18. Net worth of business and/or investment farm (FAFSA/SAR #90) If negative, enter zero.	+	
19. Adjusted net worth of business/farm (Calculate using Table 6.)	+	
20. Net worth (sum of lines 16, 17, and 19)	=	
21. Education savings and asset protection allowance (Table 7)	−	
22. Discretionary net worth (line 20 minus line 21)	=	
23. Asset conversion rate	×	**.12**
24. CONTRIBUTION FROM ASSETS If negative, enter zero.	=	

PARENTS' CONTRIBUTION		
AVAILABLE INCOME (AI) (from line 15)		
CONTRIBUTION FROM ASSETS (from line 24)	+	
25. Adjusted available income (AAI) May be a negative number.	=	
26. Total parents' contribution from AAI (Calculate using Table 8.) If negative, enter zero.		
27. Number in college in 2021–2022 (Exclude parents.) (FAFSA/SAR #73)	÷	
28. PARENTS' CONTRIBUTION (standard contribution for nine-month enrollment)*** If negative, enter zero.	=	

**Do *not* include the family's home.

***To calculate the parents' contribution for other than nine-month enrollment, see page 11.

income, assets, and other inputs and record the aid estimate that is produced, and then re-enter their inputs with a small change to income and record how predicted aid changes. In fact, even this method can prove difficult, as some colleges use a template for their NPC website that only allows the user to specify one of several income ranges, rather than inputting an exact income amount. In sum, due to the numerous barriers discussed above, it is unlikely that parents of college students know the marginal implicit tax rate from college aid that they face when making income decisions.

Figure 6: News Descriptions of College Aid Implicit Tax

4. Postpone parental income

The formula "gives you a living allowance based on taxes and household size, and then 22% to 47% of your adjusted income after that is fair game," says Mark Struthers, a financial advisor in Chanhassen, MN.

The exact amount depends on a complicated calculation that considers the parents' ages, number of children and other factors.

"As a very rough ballpark, you'll pay 20% to 25% of gross income toward college expenses if your annual family income is between $150,000 and $200,000," Struthers says.

That drops to about 5% for families earning around $50,000 and 10% for families earning about $75,000.

2. Minimize income in the base year.

The FAFSA calculates the family's financial strength using income and tax information from a previous calendar year called the base year. The base year is the prior-prior year. For example, the base year for the 2023-2024 FAFSA that students started filling out on October 1, 2022, is 2021.

Since the financial aid formula is heavily weighted toward income, it is a good idea to minimize income during the base year. For example, avoid realizing capital gains during the base year. If you must sell stocks, bonds, mutual funds, and other investments, try to offset the capital gains with losses. You can reduce your adjusted gross income (AGI) by having capital losses exceed capital gains by up to $3,000. You should also avoid taking retirement plan distributions during the base year since the withdrawals will count as income on the FAFSA, even if they are a tax-free return of contributions to a Roth IRA.

Every $10,000 reduction in parent income will increase aid eligibility by about $3,000.

Every $10,000 reduction in student income will increase aid eligibility by about $5,000.

Notes: Sources include https://money.com/more-financial-aid-money-fafsa/ and https://www.collegeavestudentloans.com/blog/file-the-fafsa-to-get-more-money-in-college.

3 A Model of Income Response to College Aid and Deadweight Loss with Misperception

3.1 Model Setup and Solution

In the model, agents value consumption and they dislike producing income. There are two periods, with period 0 representing years in which income does not affect college aid and period 1 representing years in which income does affect college aid. Each agent chooses how much income to earn in period 0 and in period 1, and their consumption is then determined by their budget constraint. Agents can misperceive the implicit tax rate on period 1 income in a heterogeneous manner.

Specifically, each agent solves the following two-period dynamic income problem:

$$\max_{C_i,\, Z_{i,0},\, Z_{i,1}} U \;=\; C_i \;-\; \sum_{t=0}^{1} \frac{a_i}{1+\frac{1}{e(X_i)}} \left(\frac{Z_{i,t}}{a_i}\right)^{1+\frac{1}{e(X_i)}} \tag{1}$$

$$\text{s.t.} \quad C_i \;=\; (1-\tau_i^b) Z_{i,0} + [(1-(\tau_i^b+\tilde{\tau}_i)] Z_{i,1}$$

where C_i is agent i's total consumption; $Z_{i,0}$ is income earned in period 0; $Z_{i,1}$ is income earned in period 1; a_i is ability; e is an elasticity parameter that is allowed to vary based on observables in the vector X_i; τ_i^b is the baseline tax rate the agent faces in both periods, representing federal and state income taxes and implicit tax rates from other social programs, all of which are the same in college and non-college years; and $\tilde{\tau}_i$ is the additional tax rate the agent *perceives* to apply to their period 1 income. The true additional tax rate the agent faces in period 1 is τ_i. For simplicity, I assume utility is quasilinear in consumption, and as a result agents are indifferent to the allocation of consumption across the two periods, which emphasizes that the problem is one of dynamic income choice rather than of consumption allocation.

I assume that each agent makes their income decisions *as if* $\tilde{\tau}_i$ is the true additional tax rate they face. If an agent misperceives this tax rate, so that $\tilde{\tau}_i \neq \tau_i$, I assume this is accounted for when the true budget constraint – which replaces $\tilde{\tau}_i$ with τ_i – binds, so that the agent's actual consumption might differ from their chosen consumption.

Taking the first order conditions and solving yields the solution for chosen income in each period as:

$$\begin{aligned} Z_{i,0} &= a_i(1-\tau_i^b)^{e(X_i)} \\ Z_{i,1} &= a_i[1-(\tau_i^b+\tilde{\tau}_i)]^{e(X_i)} \end{aligned} \tag{2}$$

In period 0, the period in which income does not affect college aid, each agent produces income that is lower than their ability a_i and depends on the baseline net-of-tax rate $(1-\tau_i^b)$. In period 1, the period in which income does affect college aid, each agent produces income that is lower than their ability and depends on the total perceived net-of-tax rate $[1-(\tau_i^b+\tilde{\tau}_i)]$. $e(X_i)$ is the elasticity of earned income with respect to the total perceived net-of-tax rate for an individual with observables X_i. Below, I refer to e as the structural elasticity, as it is the parameter that determines preferences over consumption and earning income.

3.2 Reduced Form vs. Structural Elasticity

I will distinguish between the reduced form elasticity and the structural elasticity. The reduced form elasticity corresponds to the standard ETI, which measures the change in income with respect to the true marginal tax rate. The structural elasticity instead measures the change in income with respect to the perceived marginal tax rate. The structural elasticity is solely a function of the parameters of the utility function, but the reduced form elasticity depends also on how well or poorly the family understands the tax schedule.

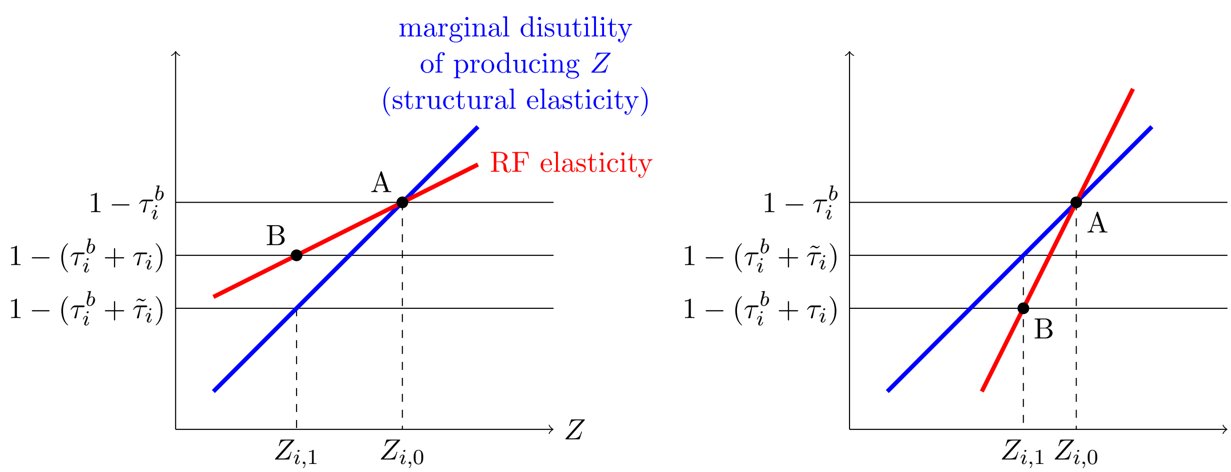
Figure 7 illustrates this distinction. The figure considers how income changes between period 0 and period 1 in the preceding model. The individual dislikes producing income at an increasing marginal disutility, but likes consumption.[6] $Z_{i,0}$ is income in period 0, which occurs where the marginal disutility of earning income equals the marginal utility of consumption, normalized to the log net-of-tax rate in period 0, $(1-\tau_i^b)$. In period 1, if the individual perceives her additional tax rate from col-

[6] Figure 7 assumes utility is quasilinear in consumption, so that the marginal utility of consumption curves are flat.

lege aid to be $\tilde{\tau} > 0$, she will choose a lower income level that equates her marginal disutility of earnings with her total perceived net-of-tax rate $[1 - (\tau_i^b + \tilde{\tau}_i)]$. This lower income level is labeled as $Z_{i,1}$ in the figure, and the blue curve traces out how income will vary with the perceived net-of-tax rate. The slope of this curve depends on the individual's utility function, and in particular on the rate at which the marginal disutility of earning declines as income falls. This is the structural elasticity.

The econometrician typically doesn't observe the perceived tax rate, but only the actual rate, τ_i^b and τ_i, along with income in each period. In other words, the econometrician observes the points labeled "A" and "B" in the data. The ETI that the econometrician will estimate (the "reduced form ETI") is the change in log earnings divided by the change in the log net-of-tax rate between the two periods, which extrapolates the line through points A and B. The left panel of Figure 7 shows a case where $\tilde{\tau} > \tau$. Here, the econometrician will estimate a larger ETI than is implied by the utility function parameters alone. The right panel shows a different case, where the structural elasticity is the same but now the $\tau > \tilde{\tau}$. Here, the econometrician's reduced form elasticity will be smaller than the structural ETI.

Figure 7: Reduced Form vs. Structural Elasticity



Notes: The figure details the relationship between the structural elasticity. In the left panel, the perceived tax rate is higher than the true tax rate. The blue curve is the structural relationship between income earned and the marginal disutility of earning income, and this curve along with the perceived tax determines income decisions. The econometrician observes data points A and B, and uses these to fit the reduced form relationship between income and the actual tax rate and therbey estimate the reduced form elasticity. In this case, the reduced form elasticity is larger than the underlying structural elasticity. The right panel shows the opposite case, where the perceive tax is lower than the true tax rate. In this case, the reduced form elasticity is smaller than the underlying structural elasticity.

The two panels in Figure 7 provide intuition to support the following result: the relationship by which the structural elasticity and the perceived tax rate determine the reduced form elasticity can be inverted, so that knowledge of the reduced form elasticity and the percieved tax rate is sufficient to identify the structural elasticity. I turn now to deriving this result formally.

In most empirical studies, the reduced form ETI estimand is an instrumental variables ratio of an average policy effect on log income scaled by the first stage average effect of the policy on the log net-of-tax rate. In such cases, the reduced form elasticity can be expressed following the notation in Figure 7 as:

$$\beta^{ETI}(X_i) \;:=\; \frac{E[\ln(Z_{i,1}) - \ln(Z_{i,0}) \,|\, X_i]}{E[\ln(1-(\tau_i^b+\tau_i)) - \ln(1-\tau_i^b) \,|\, X_i]}$$

where we allow for heterogeneity by observables in vector X_i.

We can use the solution of the preceding model as written in Equation (2) to plug in for $Z_{i,1}$ and $Z_{i,0}$ to express the reduced form ETI β^{ETI} as a function of the structural elasticity e, conditional on observables X_i:

$$\begin{aligned}
\beta^{ETI}(X_i) \;&:=\; \frac{E[\ln(Z_{i,1}) - \ln(Z_{i,0}) \,|\, X_i]}{E[\ln(1-(\tau_i^b+\tau_i)) - \ln(1-\tau_i^b) \,|\, X_i]} \\
&=\; \frac{E[\ln(a_i[1-(\tau_i^b+\tilde{\tau}_i)]^{e(X_i)}) - \ln(a_i(1-\tau_i^b)^{e(X_i)}) \,|\, X_i]}{E[\ln(1-(\tau_i^b+\tau_i)) - \ln(1-\tau_i^b) \,|\, X_i]} \\
&=\; e(X_i)\cdot\frac{E[\ln(1-(\tau_i^b+\tilde{\tau}_i)) - \ln(1-\tau_i^b) \,|\, X_i]}{E[\ln(1-(\tau_i^b+\tau_i)) - \ln(1-\tau_i^b) \,|\, X_i]}
\end{aligned}$$

As a result, we can also solve for the structural elasticity as a function of the reduced form elasticity and a measure of both the perceived and actual tax:

$$e(X_i) \;=\; \beta^{ETI}(X_i)\cdot\frac{E[\ln(1-(\tau_i^b+\tau_i)) - \ln(1-\tau_i^b) \,|\, X_i]}{E[\ln(1-(\tau_i^b+\tilde{\tau}_i)) - \ln(1-\tau_i^b) \,|\, X_i]} \tag{3}$$

Under the assumption that the baseline tax is zero, which I will maintain in subsequent sections, this simplifies to:

$$e(X_i) \;=\; \beta^{ETI}(X_i)\cdot\frac{E[\ln(1-\tau_i) \,|\, X_i]}{E[\ln(1-\tilde{\tau}_i) \,|\, X_i]} \tag{4}$$

In Section 5, I estimate the reduced form ETI with respect to the implicit tax in college aid. Then in Section 6, I administer an online survey to measure parents' perceptions of their implicit tax from aid, and I combine this with the reduced form ETI estimate to produce an estimate of the structural elasticity.

3.3 Sufficient Statistics for Deadweight Loss and The Impact of Misperception

Following the seminal work of Feldstein (1999) demonstrating that the elasticity of taxable income (ETI) is a sufficient statistic to calculate the deadweight loss (DWL) arising from a tax, the field of empirical public finance has focused largely on estimating empirical ETI's with respect to various taxes. In this section, I present a model which shows that the standard reduced form ETI is no longer sufficient for computing DWL when individuals misperceive the marginal tax rate they face; instead, one must combine the reduced form ETI with a measure of the perceived tax rate. Additionally, I derive a measure of the impact of misperception on DWL. Ultimately, DWL depends on misperception through one statistic – the average of the squared misperception parameter – which summarizes two channels. First, DWL increases as agents perceive a higher tax rate on average, as this produces a larger average distortion to income. Second, conditional on the average perceived tax rate, DWL increases with the *variance* of the misperception parameter. As described below, the intuition for this result is based on the common result that DWL increases with the square of a tax, and misperception can be viewed as an additional tax levied on top of the true tax.

In Equation (1), begin by defining the disutility function of producing income $v_i(z) \coloneqq \dfrac{a_i}{1+\frac{1}{e(X_i)}}\left(\dfrac{z}{a_i}\right)^{1+\frac{1}{e(X_i)}}$. Then the first order conditions for Equation (1) are $v_i'(Z_{i,0}) = (1-\tau_i^b)$ and $v_i'(Z_{i,1}) = [1-(\tau_i^b+\tilde{\tau}_i)]$.

To assess DWL, assume all tax revenue collected from each agent is returned to the agent as a lump sum transfer. Then the welfare (utility) of agent i is:

$$W_i \;=\; \left\{(1-\tau_i^b)Z_{i,0} \;+\; [1-(\tau_i^b+\tau_i)]Z_{i,1} \;-\; v_i(Z_{i,0}) \;-\; v_i(Z_{i,1})\right\} \;+\; \underbrace{\tau_i^b Z_{i,0} + (\tau_i^b+\tau_i)Z_{i,1}}_{\text{Lump sum transfer}}$$

We now consider how welfare changes along with the introduction of a tax $\Delta\tau_i$ for agent i. Taking the derivative of the preceding equation with respect to τ_i yields:

$$\frac{dW_i}{d\tau_i} \;=\; [1-(\tau_i^b+\tau_i)]\frac{dZ_{i,1}}{d\tau_i} \;-\; Z_{i,1} \;-\; v_i'(Z_{i,1})\frac{dZ_{i,1}}{d\tau_i} \;+\; (\tau_i^b+\tau_i)\frac{dZ_{i,1}}{d\tau_i} \;+\; Z_{i,1}$$

which simplifies to:

$$\frac{dW_i}{d\tau_i} \;=\; \frac{dZ_{i,1}}{d\tau_i}(\tau_i^b+\tilde{\tau}_i)$$

where we make use of the above first order conditions $v_i'(Z_{i,0}) = (1-\tau_i^b)$ and $v_i'(Z_{i,1}) = [1-(\tau_i^b+\tilde{\tau}_i)]$. The second derivative of welfare with respect to the tax is:

$$\frac{d^2W_i}{d\tau_i^2} \;=\; \frac{dZ_{i,1}}{d\tau_i}\frac{d\tilde{\tau}_i}{d\tau_i} \;+\; \frac{d^2Z_{i,1}}{d\tau_i^2}(\tau_i^b+\tilde{\tau}_i)$$

Then we approximate the change in welfare due to the tax using a second order Taylor expansion as is standard in the public finance literature:

$$\begin{aligned}
\Delta W_i &\approx \frac{dW_i}{d\tau_i}\Delta\tau_i + \frac{1}{2}\frac{d^2W_i}{d\tau_i^2}(\Delta\tau_i)^2 \\
&= \left[\frac{dZ_{i,1}}{d\tau_i}(\tau_i^b + \tilde{\tau}_i)\right](\Delta\tau_i) + \frac{1}{2}\left[\frac{dZ_{i,1}}{d\tau_i}\frac{d\tilde{\tau}_i}{d\tau_i} + \frac{d^2Z_{i,1}}{d\tau_i^2}(\tau_i^b + \tilde{\tau}_i)\right](\Delta\tau_i)^2 \\
&= \frac{1}{2}\left[\frac{dZ_{i,1}}{d\tau_i}\frac{d\tilde{\tau}_i}{d\tau_i}\right](\Delta\tau_i)^2
\end{aligned}$$

where the terms multiplied by $(\tau_i^b + \tilde{\tau}_i)$ drop out because we evaluate the Taylor expansion beginning from $\tau_i = 0$ and we assume there is no misperception when the true tax is zero, and also because we assume the baseline tax τ_i^b is zero. In fact, individuals face a nonzero marginal tax on income at baseline due to federal and state income taxes along with incentives created by means testing in other social programs. Assuming a baseline tax of zero here focuses the analysis on DWL that is produced directly from the implicit tax in college aid regardless of the structure of other tax programs, while omitting the portion of DWL that depends on the interaction between college aid incentives and existing programs.

Now we define the individual misperception parameter θ_i such that $\tilde{\tau}_i = \theta_i\tau_i$, which captures the degree to which an individual over- or under-estimates their own marginal tax rate. Then we can rewrite the preceding expression for the individual change in welfare as:

$$\Delta W_i = \frac{1}{2}\frac{dZ_{i,1}}{d\tilde{\tau}_i}\theta_i^2(\Delta\tau_i)^2$$

Then, the total deadweight loss in a population with a unit mass of agents is:

$$DWL = -\Delta W = \frac{1}{2}\cdot E\left[-\frac{dZ_{i,1}}{d\tilde{\tau}_i}\theta_i^2(\Delta\tau_i)^2\right] \tag{5}$$

Equation (5) demonstrates that welfare can be computed using information on the structural response of income to a change in the perceived tax, the square of the tax, and the square of the misperception parameter all at the individual level. Estimating each of these components at the individual level, however, is intractable. To facilitate estimation, I make two simplifying assumptions that reduce the degree of allowed heterogeneity.

First, I assume $Cov\left(-\frac{dZ_{i,1}}{d\tilde{\tau}_i}(\Delta\tau_i)^2, \theta_i^2\right)$ is negligible, in which case we can write:

$$DWL = \underbrace{\frac{1}{2}\cdot E\left[-\frac{dZ_{i,1}}{d\tilde{\tau}_i}(\Delta\tau_i)^2\right]}_{\text{Correct perceptions}}\cdot \underbrace{E\left[\theta_i^2\right]}_{\text{Misperception}} \tag{6}$$

Equation (6) highlights the impact of misperception on DWL. The expression is comprised of two components. First is a standard Harberger triangle expression, which corresponds to the DWL that would exist if all agents had correct perceptions.[7] The second component captures the impact of misperception on DWL. Specifically, the impact of misperception on DWL is to scale the DWL that would occur under correct perceptions by a factor equal to the average square of the misperception parameter. I return below to the intuition behind this result.

It is likely that $Cov\left(-\frac{dZ_{i,1}}{d\tilde{\tau}_i}(\Delta\tau_i)^2, \theta_i^2\right)$ is negative, so that the DWL calculations presented in Section 6.2 that assume this covariance is negligible are likely to be overestimates. This is for three reasons. First, individuals facing a higher stakes incentive – in this case, a higher marginal implicit tax rate from aid – are more likely to exert costly effort to form an accurate perception of the incentive, consistent with findings in Taubinsky and Rees-Jones (2018) and Morrison and Taubinsky (2023). A more accurate perception is reflected in θ_i^2 being closer to one. In Section 6.2, I present survey results showing that $E[\theta_i^2]$ is substantially larger than one in the college aid setting. Therefore, more accurate perceptions in the college aid setting means a lower θ_i^2 on average. Then, if those facing a higher tax rate form more accurate perceptions, there is negative correlation between $(\Delta\tau_i)^2$ and θ_i^2. Second, higher income families are more likely to have the resources and familiarity with the college process to form more accurate perceptions, and higher income families generally face a higher marginal implicit tax rate in the progressive college aid schedule, again creating negative correlation between $(\Delta\tau_i)^2$ and θ_i^2. Finally, if we allow for heterogeneous elasticities, it is likely that more elastic families will exert costly effort to form an accurate perception of their tax rate, because the information is more relevant to their behavior. This would induce a negative correlation between $-\frac{dZ_{i,1}}{d\tilde{\tau}_i}$ and θ_i^2. If $Cov\left(-\frac{dZ_{i,1}}{d\tilde{\tau}_i}(\Delta\tau_i)^2, \theta_i^2\right)$ is negative, then the estimates of the impact of misperception on DWL that I report in Section 6.2 are overestimates.

Second, I incorporate the assumption that the structural elasticity is constant conditional on the covariate vector X_i.

$$\begin{aligned}
DWL &= \frac{1}{2} \cdot E\left[-\frac{dZ_{i,1}}{d\tilde{\tau}_i}(\Delta\tau_i)^2\right] \cdot E[\theta_i^2] \\
&= \frac{1}{2} \cdot E\left[e(X_i)Z_{i,1}\frac{1}{1-(\tau_i^b+\tilde{\tau}_i)}(\Delta\tau_i)^2\right] \cdot E[\theta_i^2] \\
&= \frac{1}{2} \cdot E\left[e(X_i)Z_{i,1}(\Delta\tau_i)^2\right] \cdot E[\theta_i^2]
\end{aligned}$$

[7] Note that under correct perceptions, $\frac{dZ_{i,1}}{d\tilde{\tau}_i} = \frac{dZ_{i,1}}{d\tau_i}$ and $E[\theta_i^2] = 1$, leaving $DWL = \frac{1}{2} \cdot E\left[-\frac{dZ_{i,1}}{d\tilde{\tau}_i}(\Delta\tau_i)^2\right] = \frac{1}{2} \cdot E\left[-\frac{dZ_{i,1}}{d\tau_i}(\Delta\tau_i)^2\right]$, which is the standard Harberger triangle expression.

where the last step uses the assumption that the baseline tax τ_i^b is zero and the fact that we evaluate the Taylor expansion from a beginning tax of $\tau_i = 0$, along with the assumption that $\tilde{\tau}_i = 0$ as well when $\tau_i = 0$. $Z_{i,1}$ appears in the final expression above as a weight on the elasticity $e(X_i)$, which accounts for the fact that, conditional on X_i, individuals with a higher baseline income $Z_{i,1}$ will reduce income by a greater amount under a constant elasticity conditional on X_i.

Expressing the structural elasticity as a function of the identifiable measures of the reduced form elasticity and perceived and actual tax rates as in Equation (4) yields the final estimable expression for DWL:

$$DWL = \underbrace{\frac{1}{2} \cdot E\left[\beta^{ETI}(X_i)\frac{E[\ln(1-\Delta\tau_i) \mid X_i]}{E[\ln(1-\Delta\tilde{\tau}_i) \mid X_i]} Z_{i,1}(\Delta\tau_i)^2\right]}_{\text{Correct Perceptions}} \cdot \underbrace{E[\theta_i^2]}_{\text{Misperception}} \tag{7}$$

again making use of the assumption that the baseline tax τ_i^b is zero.

Equation (7) is the key result. This result forms the basis for the empirical exercise in Section 6.2, where I report estimates of the average DWL due to the college aid implicit tax on income that would occur with or without misperception.

I now return to the result that misperception causes DWL to be scaled by a factor equal to the average square of the misperception parameter. To understand the intuition behind this result, observe that we can write the proportional increase in DWL due to misperception as:

$$\underbrace{(E[\theta_i^2] - 1)}_{\text{Proportional increase in DWL due to misperception}} = \underbrace{(E[\theta_i]^2 - 1)}_{\text{Bias}} + \underbrace{Var(\theta_i)}_{\text{Variance}} \tag{8}$$

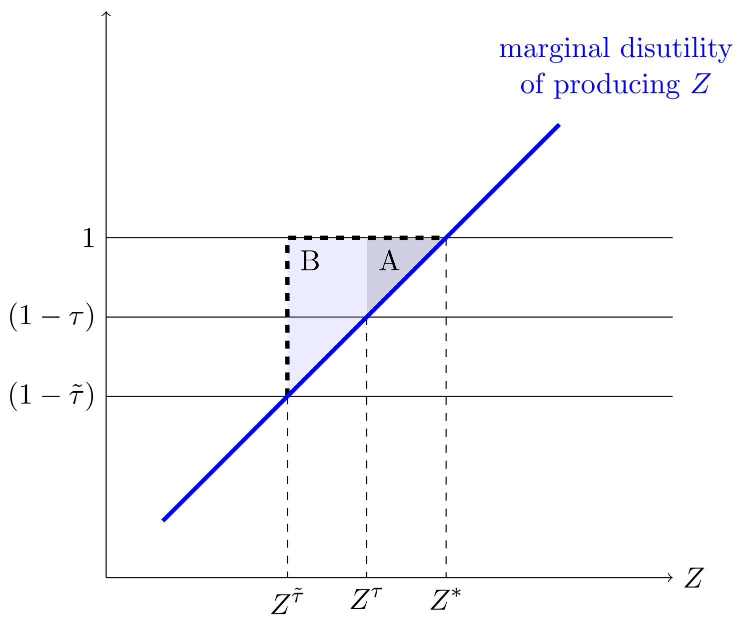
Misperception therefore affects DWL through two channels. First, DWL is higher (lower) due to misperception when the average misperception parameter is above (below) one, reflecting that individuals on average perceive a tax rate that is higher (lower) than the true rate, as this leads to a larger (smaller) distortionary reduction of income on average. This is the bias channel. Second, conditional on the average level of misperception, DWL increases with the *variance* of misperception. This result is consistent with recent results in Taubinsky and Rees-Jones (2018) and Taubinsky and Morrison (2023), which study the impact of heterogeneous salience of a sales tax on welfare.

To see why DWL increases with the variance of misperception, consider Figure 8. Assume there are two agents with the same structural curve of marginal disutility of producing income Z who both face a true tax τ. In the first scenario, assume both agents correctly perceive the tax and choose income Z^τ. This produces total DWL of $2A$.[8] In the second scenario, assume one agent misperceives the

[8] Recall that under the maintained assumption of quasilinear utility, the marginal utility of consumption is constant, which we set equal to one.

tax as $\tilde{\tau} = 2\tau$, and the other agent misperceives the tax as zero. The first agent chooses income $Z^{\tilde{\tau}}$, contributing DWL equal to B, the area of the larger triangle. The second agent chooses income Z^* and contributes zero DWL, making the total DWL in this scenario equal to B. In both scenarios, the average perceived tax equals the true tax τ. However, DWL in the second scenario with higher variance of misperceptions is *twice* that of the first scenario. The intuition for this result can also be seen in Figure 8. Increasing one agent's perceived tax above τ produces a first order increase in DWL, while reducing the other's perceived tax below τ does not produce an offsetting first order reduction in DWL. This relates to the common result that DWL increases with the square of the tax rate, where misperception can be viewed equivalently to an additional tax levied on top of the pre-existing true tax – it is the average of this square, not the square of the average, that determines DWL.

Figure 8: Deadweight Loss with Misperception



Notes: The figure depicts a hypothetical marginal disutility of earning income curve alongside choices of income and deadweight loss triangles that result when the agent perceives a tax rate of zero, the true tax τ, or a higher tax $\tilde{\tau}$.

Whether misperception increases, decreases, or has no effect on DWL is ambiguous a priori. Misperception increases DWL when $E[\theta_i^2]$ is greater than one, which occurs when individuals perceive a higher tax rate than the true tax on average ($E[\theta_i] > 1$) regardless of the variance of perceptions, or when individuals perceive the tax rate to be equal to or lower than the true tax on average and the variance of misperceptions is sufficiently large as to raise $E[\theta_i^2]$ above one. Misperception decreases DWL when $E[\theta_i^2]$ is less than one, which occurs when individuals perceive a lower tax rate than the true tax on average and the variance of misperceptions is sufficiently small as to leave $E[\theta_i^2]$ below one. Misperception has no impact on DWL when $E[\theta_i^2]$ equals one, which occurs when all individuals correctly perceive the tax, or when the average perceived tax is below the true tax and the variance of misperceptions exactly offsets this.

In Section 5, I estimate the reduced form ETI with respect to the college aid implicit tax using administrative FAFSA data. Then in Section 6 I use an online survey to directly measure parents' perceptions of the college aid implicit tax schedule, which allows me to identify the structural elasticity, the degree to which DWL is increased or reduced due to misperception in the college aid setting, and the separate contributions to DWL from the bias and variance channels described above.

4 Data

4.1 FAFSA Financial Aid Application Data

To estimate the reduced form ETI with respect to the college aid implicit tax, I draw on administrative Free Application for Federal Student Aid (FAFSA) data maintained by the California Student Aid Commission (CSAC), the agency that is responsible for administering state financial aid for college students in California. FAFSA data allows me to observe essentially all the information that will affect financial aid for most students, including parent income and other inputs. The FAFSA data covers all students who file a FAFSA and (i) attended a California high school, regardless of where they attend college, or (ii) attend college in California, regardless of where they attended high school. The data spans academic years 2010-11 through 2021-22.

For the purposes of this analysis, I restrict the sample to California resident, dependent students. Non-California residents are ineligible for much of the grant aid that in-state students receive at California colleges, and thus face much lower effective marginal tax rates when attending California colleges. I restrict to dependent students (younger than 24, unmarried, without dependents) because they account for the majority of students at four-year colleges, and because parent income does not affect financial aid for independent students who face a very different set of aid incentives. Most undergraduate students who attend a four-year college directly after high school will qualify as dependent students.

There are four challenges to estimating the elasticity of income with respect to the college aid implicit tax in FAFSA data. First is that I don't directly observe aid or the implicit marginal tax rate on aid. To overcome this, I encode the EFC formula for all years from 2010-11 through 2021-22. The EFC formula relies solely on inputs from the FAFSA, so I then apply the encoded EFC formulas to the FAFSA data to calculate each student's EFC in each year. I then take the numerical derivative of aid by re-computing EFC after increasing parent income by \$100. I assume that each \$1 increase in EFC corresponds to a \$1 reduction in aid, and I scale the change in EFC by the \$100 difference in parent income to measure the marginal implicit tax rate on parent income faced by an individual student.

This will identify a family's marginal tax rate if the EFC maps one-to-one into student aid. This is not always the case. For example, not all colleges meet full need (cost of attendance minus EFC) with grants and scholarships; colleges can also offer loans to make up the difference between cost of attendance and EFC. To the extent that loans are phased out with the marginal dollar of parent income instead of grants being phased out, my estimates of marginal implicit tax rates will be overestimates, and in turn my estimates of the elasticity of taxable income will be underestimates.

Second, FAFSA data is at the student by year level, while parent income might be subject to aid incentives from more than one child in college simultaneously. The FAFSA data includes hashed records of parent identifiers on each student's FAFSA, such as name and social security number (SSN). I use the hashed parent identifier data to link together students with the same parents, and the following analysis takes place at the level of the family, which is used to mean a unique set of parents. For example, if parents face a 15% implicit marginal tax rate on aid from one child and a 15% marginal implicit tax rate from another child, they are assigned a total implicit marginal tax rate of 30%.

Third, I don't directly observe college enrollment. Students list as many as 10 potential colleges on their FAFSA to receive their FAFSA information. A common pattern in the FAFSA data is to observe a student listing multiple schools in their first year of FAFSA filing, and then in subsequent years list only one school, which was observed in the set of schools listed in the first year. In these common cases, I assume that in the first year the student is enrolled at the single school that is listed in the second year. In all cases when a student only lists one school, I assume the student attends that school.

Finally, the fourth challenge is that I only observe income in years that affect financial aid and so are subject to the implicit tax from aid. This presents a challenge to identifying the causal response of parent income to the college aid implicit tax. As described further in the next section, I exploit the "prior-prior" policy shift of the income base year in order to observe one year of income in the FAFSA data that was not anticipated to affect aid and would have been treated as untaxed.

In Section 5, I present estimates of the ETI that restrict to students enrolled at a public four-year college in California (UC or CSU) or at a private not-for-profit four-year college anywhere in the US. This excludes all for-profit colleges, which have very different pricing models, and public four-year colleges outside California. Across the US, public colleges offer different aid packages to in-state compared with out-of-state students, and generally out-of-state students receive significantly lower aid in general and face less phaseout as a consequence. Therefore, the main sample of students attending a public four-year college in California or a private college anywhere in the US is the largest set of colleges at which California resident students can expect to face an aid schedule with phaseout similar to those described by Figure 2. In the Appendix, I report results from a sample that further restricts to only those enrolled at public four-year colleges in California (UC or CSU). These colleges have aid schedules that more closely match the EFC formula, so that my EFC-based measure of a family's marginal implicit tax rate is likely to be more accurate.

The measure of parent income that is relevant to financial aid can be summarized as total pre-tax income including several categories excluded from the US federal income tax. This income measure begins with adjusted gross income (AGI) for tax filers or total wage income for non-filers. It then adds income that is typically excluded from the US federal income tax including payments to tax-deferred pension and retirement savings plans, IRA deductions, untaxed portions of IRA or pension distributions, child support received, tax exempt interest income, allowances paid to the military or clergy, veterans noneducation benefits, and other sources of untaxed income such as workers' compensation, disability benefits, or untaxed portions of health savings account contributions.[9][10]

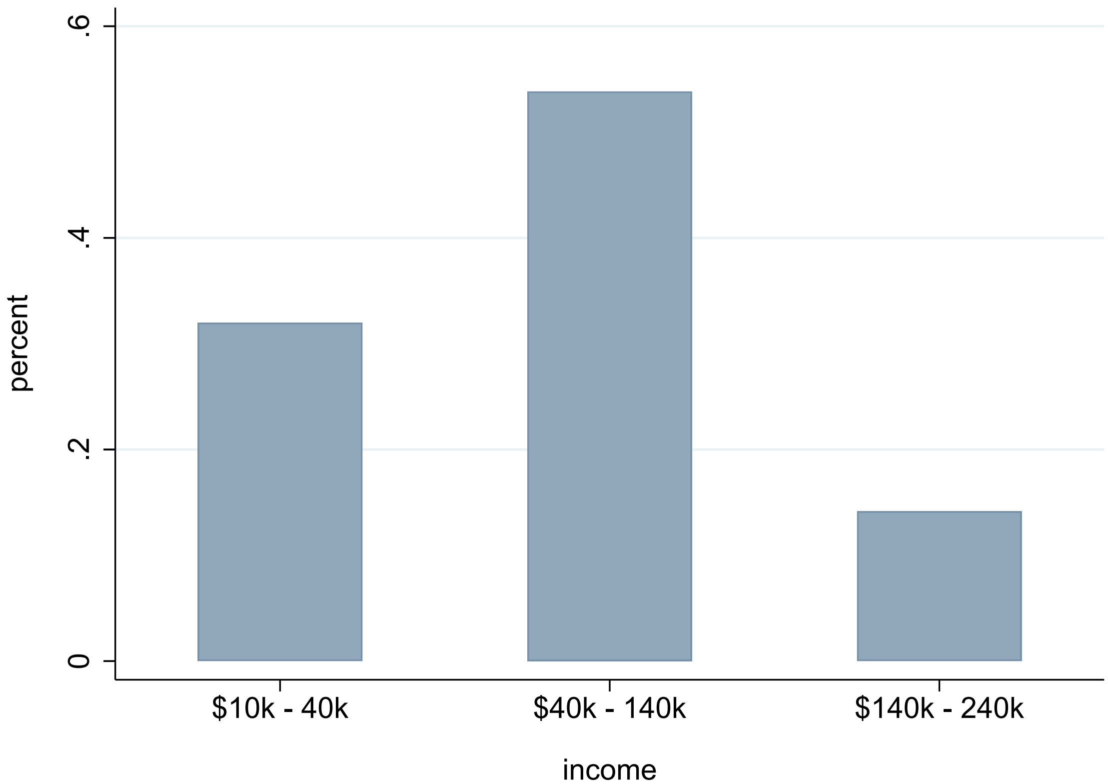
Figure 9 plots the distribution of parent total income in FAFSA data across three income bins: \$10k-40k (low), \$40k-140k (middle), and \$140k-240k (high). The majority of observations are in the middle income bin. The low income bin is also well populated. Higher incomes are relatively less common in the FAFSA data, so estimates for this group are generally less precise. It is worth noting that there is an incentive to file a FAFSA even for families whose income is high enough to disqualify them from receiving grant aid. Filing a FAFSA is a requirement to be eligible for federal student loans, which are offered at favorable rates and payback terms.

Table 1 lists descriptive statistics for the FAFSA data, split by low, middle, and high bins of total income. The table includes data from all years 2010 through 2021 for observations that have all information needed to construct the MTR estimate, and for which enrollment only occurs at a California public four-year university or a private four-year university regardless of location. Families with a high share of income coming from non-labor sources make up approximately 15% of observations, with little variation by income group. The share with high assets is strongly increasing in income, increasing from 2% for low income families to 11% for middle income families and 31% for high income families.

[9] Under the FAFSA Simplification Act passed on Dec. 27, 2020, the definition of total income used aid calculations will change beginning with the 2024-25 academic year. The most significant change to the total income measure used for aid is that payments made to tax-deferred pension and retirement savings plans will no longer be included in total income.

[10] The marginal implicit tax rate from college aid differs between income counted under AGI and income that is excluded from the US federal income tax but counted in the EFC formula, for example contributions to tax-deferred pensions and retirement savings plans. The is because the EFC formula includes an allowance for federal income tax amount paid, which is subtracted from total income. If a parent earns \$1 more in pre-tax AGI, the portion of this dollar that is paid in incremental federal income taxes is excluded from the college aid implicit tax, so that the marginal implicit tax on pre-tax AGI is slightly lower than that on income excluded from the federal income tax. My measure of the marginal implicit tax rate from college aid in Section 5 matches the marginal implicit tax rate on pre-tax AGI by accounting for the marginal increase in federal income tax liability that will not affect aid. To the extent that families' marginal dollar of total income is in a category not subject to the federal income tax, my measure of the marginal implicit tax from college aid will slightly understate the true value.

Figure 9: Income Distribution in FAFSA Data



Notes: The figure shows the percent of family-year observations in the FAFSA data in each income bin.

Just over 90% of all families have only one child enrolled in a given year, with higher income families slightly more likely to enroll two children simultaneously. The average cost of attendance is approximately $30k overall, with higher income families facing a slightly higher cost of attendance, which reflects a combination of enrollment patterns and differences in number of children enrolled. Financial aid is decreasing in income, from $18k for low income families to $11k for middle income families and $2k for high income families on average. As a result, net cost after aid is increasing with income, from $11k for low income families to $20k for middle income families and $34k for high income families. The average marginal implicit tax rate on income from aid is 3pp for low income families, 13pp for middle income families, and 4pp for high income families. A significant portion of the variation in MTR's across income groups is due to the fraction facing zero MTR – families with income that is either below or above the phaseout region. The share facing a positive MTR from aid is 22% for low income families, 61% for middle income families, and 15% for high income families. Among families facing a positive MTR, the MTR is increasing with income, from 15pp for low income families to 21pp for middle income families and 23pp for high income families.

Table 1: FAFSA Descriptive Statistics by Parents' Total Income

	\$10k - 40k (27%)		\$40k - \$140k (58%)		\$140k - \$240k (15%)	
	Mean	SD	Mean	SD	Mean	SD
Characteristics						
Total income	\$24,850	\$8,572	\$81,317	\$27,364	\$176,252	\$26,677
Share with high non-labor income	0.17	0.37	0.13	0.34	0.15	0.35
Share with high assets	0.02	0.15	0.11	0.31	0.31	0.46
Share with…						
1 enrolled	0.94	0.24	0.92	0.27	0.89	0.31
2 enrolled	0.06	0.24	0.08	0.27	0.10	0.31
3 enrolled	0.00	0.05	0.00	0.05	0.00	0.06
Cost, aid, and MTR						
Cost of attendance	\$28,807	\$15,523	\$31,053	\$17,002	\$36,675	\$19,466
Financial aid	\$17,570	\$14,541	\$10,805	\$14,098	\$2,481	\$8,242
Net cost after aid	\$11,236	\$3,471	\$20,248	\$9,156	\$34,193	\$14,846
Marginal implicit tax rate from aid	0.03	0.07	0.13	0.12	0.04	0.09
Share with positive MTR	0.22	0.42	0.61	0.49	0.15	0.36
MTR conditional on positive	0.15	0.07	0.21	0.08	0.23	0.08
N	372,074		790,882		205,464	

Notes: Summary statistics are shown for family-year observations from 2010 through 2021, among observations for which no variables are missing.

In Section 5, I use the same total income measure that is relevant to financial aid calculations in all of my empirical analysis.

4.2 Online Survey Data

In order to identify the structural elasticity and the impact of misperception on DWL, I administer an online survey to directly measure parents' perceptions of the college aid implicit tax schedule. The survey was administered through Prolific Academic, a website that connects survey administrators with survey takers, between September 26, 2023 and October 19, 2023. The survey targeted parents with a child born between the years 2001 and 2023, so that the child would be between age 0 and 22 at the time the survey. The survey instructed the respondent to consider one child in particular and to answer all questions with regard to that child. Additional screeners for eligible participants included US nationality and fluency in English. The sample includes respondents from across the US and is not probability weighted. In total, 3,158 respondents completed the survey. The median survey completion time was 12.5 minutes, and each respondent was paid between \$3 and \$4. All survey responses are anonymous.

The survey asks each respondent for their best guess of average financial aid provided to an in-state student attending a public four-year college in the respondent's current state with varying levels of family income, alongside various demographics including previous year income, total savings, age, and state. Crucial for the empirical design implemented below, the survey includes two separate elicitations of a respondent's perception of the college aid implicit tax schedule. First, the respondent is asked for their best guess of aid provided to an in-state student whose total parent income is \$45k, \$55k, \$65k, or \$75k. Then, beginning on a separate screen, the respondent is asked for their best guess of average aid provided to in-state students with family income in each of the following bins: \$0-30k, \$30-48k, \$48-75k, \$75-110k, and above \$110k. These income bins correspond to the bins for which colleges report publicly available statistics on average aid through IPEDS, the same data used in Figure 2.

I use the respondent's best guesses of aid across income levels to construct two measures of the respondent's perceptions of the marginal implicit tax schedule from college aid. First, I take the difference between the respondent's guesses of aid for a student with parent income of \$75k or \$45k and divide by the income difference of \$30k, producing a measure of the perceived marginal implicit tax rate in this income range which I will refer to as $\tilde{\tau}_i^{4575}$.[11] Then I produce a measure of the respondent's perception of their own marginal implicit tax rate that can be compared against the IPEDS aid statistics, so that I can measure a respondent's misperception of their own marginal implicit tax rate. I begin by matching each respondent to the nearest of the five IPEDS income bins based on the respondent's previous year total household income. I then take the difference in the respondent's guess of average aid in their matched income bin and the income bin just below, and I divide this number by the difference in median incomes across the two income bins. For example, if a respondent's income is \$60k, I would match them to the \$48-75k bin, I would compute the difference in their guesses of aid for the \$30-48k and \$48-75k bins, and I would divide this difference by \$61.5k - \$39k = \$22.5k. This produces my measure of a respondent's own perceived marginal implicit tax rate, $\tilde{\tau}_i$. I then measure the respondent's true marginal implicit tax rate τ_i by taking the difference in actual aid across the same two income bins as reported by IPEDS and scaling by the same difference in median incomes. Following Section 3.3, I then define the individual's misperception parameter as $\theta_i = \frac{\tilde{\tau}_i}{\tau_i}$. I restrict the survey data to respondents whose total household income last year was less than \$110,000, so that each respondent can be matched to an IPEDS income bin and can be assigned values for τ_i, $\tilde{\tau}_i$, and θ_i.[12]

Table 2 lists descriptive statistics for the subsample of survey respondents for whom I construct measures of the true marginal implicit tax rate from aid (τ_i), the perceived rate ($\tilde{\tau}_i$), and the misperception parameter which equals the ratio of these two (θ_i). Average income (among the subsample with income below \$110k) is \$60k, and 44% of respondents have completed a bachelor's degree. The average

[11] I construct all marginal tax rates so that a positive value means aid is reduced as income increases.

[12] I exclude the "above \$110k" IPEDS income bin because making inferences about an individual's marginal implicit tax rate from aid in this range based only on the change in average aid across income bins depends more heavily on the conditional distribution of income for those in this bin.

respondent is 39 years old, and the average age of their oldest child 22 or under – their next child who might attend college as a dependent student – is 12. The last three rows of Table 5 preview the main survey results. Misperception on average is very small. The average marginal implicit tax rate (MTR) from aid is 11%, and the average respondent's guess of their MTR from aid is 11%. The average misperception parameter – the ratio of perceived MTR to true MTR – is 1.03. However, there is high variance to misperception. While the standard deviation of true MTR's is 0.06, the standard deviation of respondent's guesses of their MTR is ten times this amount at 0.61. The standard deviation of the misperception parameter is correspondingly large at 4.07 relative to a mean of 1.03. These basic descriptive statistics suggest the following: (i) the reduced form elasticity will not differ dramatically from the structural elasticity; (ii) DWL is increased due to misperception; and (iii) the increase in DWL due to misperception is entirely a result of the high variance of misperception rather than misperception on average.

Table 2: Survey Descriptive Statistics

	Mean	SD
Total income	$59,623	$28,418
Respondent BA	0.44	0.50
Respondent age	39.2	8.9
Age of oldest child 0-22	11.5	5.8
Own aid MTR, true	0.11	0.06
Own aid MTR, guess	0.11	0.61
Ratio of MTR guess to true	1.03	4.07
N	1,886	

Notes: Observations are restricted to respondents who report an income from last year less than or equal to $110,000.

5 Empirical Analysis of the Reduced Form Elasticity of Taxable Income

5.1 Income Response to the First Year of Means Testing – Middle Income Families

5.1.1 Empirical Strategy

The primary challenge to identifying the response of income to the first year of means testing in FAFSA data is that all observations of income correspond to a year in which income was ultimately used to determine financial aid. As a result, the data contain no observations of income in years that are not subject to the college aid implicit tax, which could otherwise be used in an event study or difference-in-differences design around the first year of means testing.[13]

To overcome this challenge and identify the reduced form response of income to the first year of college aid means testing, I estimate a difference-in-differences specification that exploits a surprise policy shift of the first base year for one entering cohort, which caused families in this cohort to report one year of income they would not have anticipated as being relevant to college aid. I then use a simulated instruments approach to scale the reduced form income response by the estimated marginal net-of-tax rate in order to produce an estimate of ETI. I estimate the reduced form response and the ETI conditional on low, middle, and high baseline income groups.

Table 3 shows the base year of income used to determine financial aid for each academic year from 2014-15 through 2019-20. Until and including the 2016-17 academic year, each FAFSA asked for income from one year prior; for example, the 2016-17 FAFSA asked for income earned in 2015. Beginning with the 2017-18 academic year and in place through the present, the FAFSA asks for income from two years prior; for example, the 2017-18 FAFSA also asked for income earned in 2015. This policy change, known as "prior-prior", was announced on September 13, 2015. As a result, families with a child beginning enrollment in 2017-18 would have earned income through most of 2015, their first base year, without knowing this income would be used to determine aid. The key intuition for my empirical design is that 2015 income was effectively understood not to be subject to college aid incentives for the 2017-18 cohort, but this income is observable in the FAFSA data because it ultimately was used to determine aid. This allows me to estimate the response of income to the college aid implicit tax in a difference-in-differences design around the first year of *anticipated* college aid means testing.

Table 3: Policy Shift of Base Year

Academic year	**2014-15**	**2015-16**	**2016-17**	**2017-18**	**2018-19**	**2019-20**
Base year, old rule	2013	2014	2015	2016	2017	2018
Base year, actual	2013	2014	2015	2015	2016	2017

Notes: For each academic year from 2014-15 through 2019-20, the table shows the counterfactual income base year if the prior-prior policy were never introduced, alongside the actual base year. The highlighted base year for 2017-18 is the first instance in which the prior-prior policy went into effect, which shifted the base year back by one.

Table 4 illustrates the difference-in-differences design. The design compares changes in income from 2015 to 2016 between the 2016-17 (control) and 2017-18 (treated) entering cohorts. For each year of income beginning with 2015, the first panel of Table 4 indicates with an "X" whether families in each

[13] Gebbia et al. (2023) use federal income tax data and estimate an event study of parent income around the first year of means testing for college aid. Their reduced form results are similar to those presented in this paper, which are based on FAFSA data and a slightly different design.

cohort would have anticipated that income earned in that year would be used to determine their aid. Families in the 2016-17 cohort would have anticipated that income earned both in 2015 and in 2016 would affect their aid, and as such faced no change in the college aid incentives they understood to affect their income. Families in the 2017-18 cohort would not have anticipated that income earned in 2015 would affect their aid but would have anticipated that income earned in 2016 would affect their aid, and as such faced the introduction of anticipated college aid incentives beginning in 2016. The first panel of Table 4 additionally highlights in blue years of income that are observed in FAFSA data. Both 2015 and 2016 are observed for the 2016-17 and 2017-18 cohorts – critically, 2015 income is observed for the 2017-18 cohort due to the surprise "prior-prior" policy shift of the base year, causing the 2017-18 cohort to report income from 2015 even though they were not aware this would be the case until September 13, 2015. The difference-in-differences comparison is highlighted in a red box: I compare the change of income from 2015 to 2016 in the treated 2017-18 cohort who anticipated 2016 to be the first year of income that would affect their aid against the same change in income in the control 2016-17 cohort who correctly anticipated no change in college aid incentives between the two years.

Table 4: DiD Comparison Cohorts

Year of income	2015	2016	2017	2018	2019
Expected aid base year (substitution effect)					
2016-17 cohort: Control	X	X	X		
2017-18 cohort: Treated		X	X	X	
Paying for college (wealth effect)					
2016-17 cohort: Control		X	X	X	
2017-18 cohort: Treated			X	X	X

= observed in FAFSA data

Notes: This table details the difference-in-differences design used to estimate the ETI for middle income families in the first base year. For each year from 2015 to 2019, the top panel marks with an "X" observations in which income is used to determine aid, separately for the control 2016-17 cohort and the treated 2017-18 cohort. Instances observed in FAFSA data are shaded in blue. The red box highlights the difference-in-differences comparison. I compare the change in income from 2015 to 2016 for the treated cohort who are newly exposed to the college aid implicit tax against the control cohort who face no change in incentives. The bottom panel considers the potential timing of liquidity-induced wealth effects. The treated cohort is not yet paying for college in 2015 or in 2016. The control cohort begins paying for college in the second half of 2016, which could induce a confounding wealth effect. The empirical results do not show clear evidence of any confounding wealth effect, as discussed in Section 5.1.3.

Specifically, I estimate the reduced form response of income to the introduction of the college aid implicit tax in the following difference-in-differences (DiD) regression:

$$\ln(TI_{i,2016}) \; - \; \ln(TI_{i,2015}) \; = \; \alpha^{RF} \; + \; \beta^{RF} \cdot treated_i \; + \; \epsilon_i \tag{9}$$

where $TI_{i,t}$ is taxable income[14] on the FAFSA for family i in year t; the sample includes families in the 2016-17 and 2017-18 cohorts with a student who remains enrolled for at least three consecutive years after beginning; and $treated_i$ is an indicator for being in the 2017-18 cohort, who anticipated being newly introduced to college aid incentives beginning in 2016, as opposed to being in the 2016-17 cohort, who anticipated both 2015 and 2016 as years in which income would affect college aid. Equation (9) identifies the reduced form effect of the (anticipated) introduction of the college aid implicit tax on income, β^{RF}, under a parallel trends assumption.

The ETI depends not only on the reduced form response of income, but also on the anticipated change in the net-of-tax rate to which families are responding. Recall the intuition that the 2017-18 cohort would have anticipated income in 2016 to affect college aid, but would not have anticipated 2015 to affect aid, even though both 2015 and 2016 ultimately did affect their aid. It is helpful to define notation to make this explicit. Let $\tau_{i,t}$ be the true marginal implicit tax rate from college aid, and let $\iota_{i,t}$ be the anticipated marginal implicit tax rate, such that $\iota_{i,t} = \tau_{i,t}$ when income is correctly anticipated to affect aid, and $\iota_{i,t} = 0$ when income is not anticipated to affect aid. Further, let $\hat{\iota}_{i,t}$ be the simulated anticipated marginal implicit tax rate from college aid, which is equal to $\tau_{i,t-1}$ when income in t is correctly anticipated to affect aid. Then, the analogous DiD regression to estimate the first stage effect of the introduction of the college aid implicit tax on the anticipated log net-of-tax rate is:

$$\ln(1 - \hat{\iota}_{i,2016}) \; - \; \ln(1 - \iota_{i,2015}) \; = \; \alpha^{FS} \; + \; \beta^{FS} \cdot treated_i \; + \; \nu_i \tag{10}$$

In the control 2016-17 cohort, for whom both income earned in 2015 and in 2016 was anticipated to affect college aid, $\hat{\iota}_{i,2016} = \iota_{i,2015} = \tau_{i,2015}$; in other words, the control 2016-17 cohort by definition faced no anticipated change in their (simulated) log net-of-tax rate. In the treated 2017-18 cohort, for whom income earned in 2015 was not anticipated to affect college aid but income earned in 2016 was expected to affect college aid, $\hat{\iota}_{i,2016} = \tau_{i,2015}$ and $\iota_{i,2015} = 0$ because 2015 was not anticipated to affect aid. Therefore, the left side of Equation (10), $\ln(1 - \hat{\iota}_{i,2016}) - \ln(1 - \iota_{i,2015})$, equals zero for the control 2016-17 cohort reflecting no anticipated change in their (simulated) log net-of-tax rate, and it equals the true log net-of-tax rate on 2015 income $\ln(1 - \tau_{i,2015})$ for the treated 2017-18 cohort reflecting the anticipated introduction of the college aid implicit tax.

[14] Specifically, $TI_{i,t}$ is the "total income" concept described in Section 4.1. I describe this concept here as "taxable income" as this is the income definition that is subject to the college aid implicit tax.

The ETI is then the ratio of reduced form to first stage:

$$\beta^{ETI} = \frac{\beta^{RF}}{\beta^{FS}} \tag{11}$$

I estimate β^{ETI} by 2SLS.

I estimate the reduced form, first stage, and the ETI separately by three bins of baseline 2015 income: low ($10k - 40k), middle ($40k - 140k), and high ($140k - 240k). The college aid implicit tax primarily affects the middle income range.

5.1.2 Results

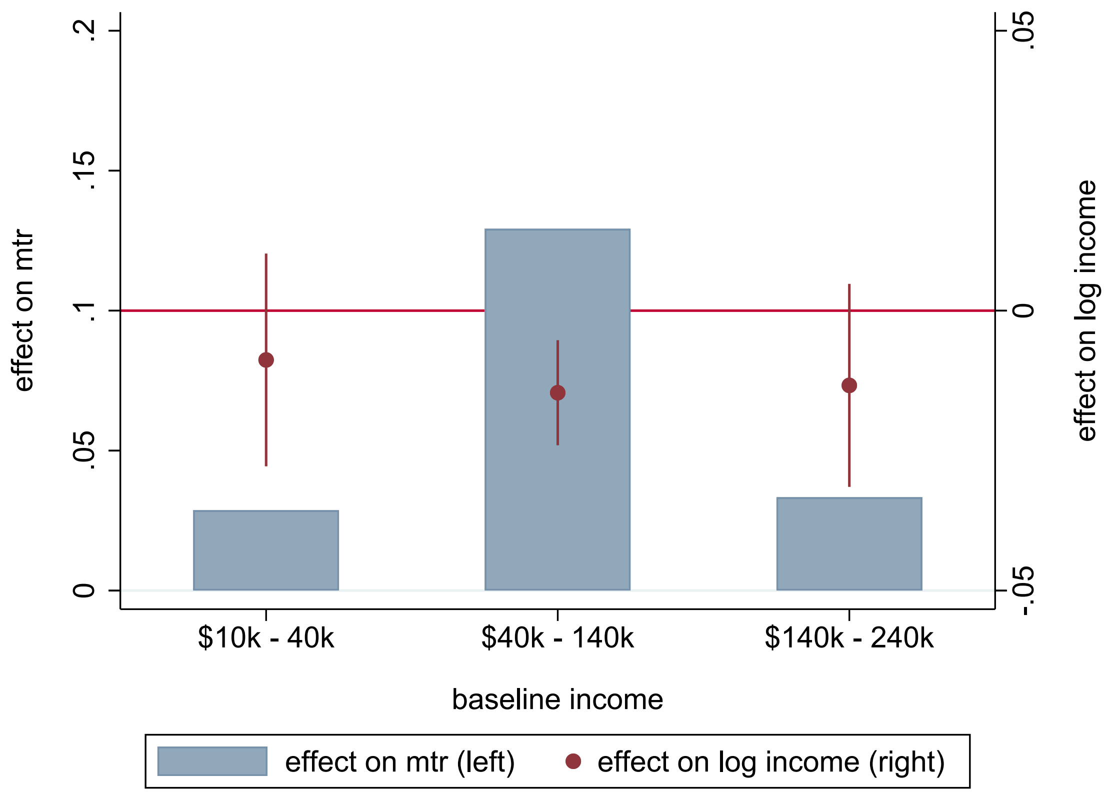
For each of the low, middle, and high baseline income groups, Figure 10 shows the reduced form effect on parent income in the first base year overlaid against the first stage effect on the marginal implicit tax rate. As expected, the average first year marginal implicit tax rate is highest for the middle income group at 13%, with the low and high income groups facing much smaller marginal implicit tax rates of about 3%. In the middle income group, being newly exposed to the college aid implicit tax causes parents to reduce income by 1.5%. However, the estimated effect on income is small and statistically insignificant for both the low and high income groups, consistent with the less dramatic marginal implicit tax rates they face.

Because the middle income group is most affected by the college aid implicit tax and in turn is the only group to show a statistically significant effect on income, I estimate the ETI only within this group. Table 5 reports point estimates and standard errors for the first base year reduced form effect on parent income, first stage effect on the log net-of-tax rate, and finally the ETI, all within the middle income group. In the reduced form, middle income families reduce income by 1.5% in response to the introduction of the college aid implicit tax. This occurs as the log net-of-tax rate falls by 0.15 in the first stage. Taking the ratio of the reduced form to the first stage, the ETI is 0.10.

Two heterogeneity splits are important to highlight. First, I consider whether families with more flexible sources of income have a higher ETI. I split the sample into families with low or high non-labor income in the baseline year 2015. Non-labor income is defined as sources of income in AGI outside of wages, self-employment income, or business income.[15] Examples of non-labor income include capital gains, interest, dividends, rental income, retirement income, or transfer payments. I define a family as high non-labor income if income from wages, self-employment, or business ownership accounts for less

[15] The FAFSA asks separately for AGI and for each parent's income earned from work, which is specified to include income from wages, self employment, or business ownership.

Figure 10: First Base Year Effect on MTR and Income



Notes: Separately by baseline income, the figure shows the first stage effect of the first base year on the simulated marginal tax rate from aid as bars (left axis) and the effect on log income in dots (right axis) with robust 95% confidence intervals.

than 80% of AGI. Families with high non-labor income exhibit an ETI substantially larger than the aggregate ETI at 0.47, just under five times the aggregate ETI. Second, I consider whether families with greater assets have a higher ETI, for example because credit constraints prevent those with lower assets from reducing income. I split the sample into families with high or low assets at the time of filing the 2017-18 FAFSA, where high assets is defined as a value of cash, savings, and checking accounts plus any investments of at least $75k.[16] Families with high assets exhibit an ETI that is nearly four times the aggregate ETI at 0.36. Neither the higher ETI for families with a high share of non-labor income nor for families with high assets is due solely to correlation between non-labor income share and assets, as the ETI for families with a high share of non-labor income and low assets is 0.42, and for families with a low share of non-labor income and high assets it is 0.27.

[16] I selected $75k as the cutoff because it is the lowest available threshold for which I can reliably observe if assets are below the threshold for any observation in my data. FAFSA has an assets threshold below which assets do not need to be reported, and the threshold varies by year and parent age. The maximum asset threshold during my sample window is $74k.

Table 5: First Base Year Elasticity of Taxable Income – Middle Income Families

		By non-labor income share		By assets		By non-labor income share and assets			
	Full sample	High	Low	High	Low	High, low	Low, high	Low, low	High, high
RF	-0.015	-0.067	-0.009	-0.039	-0.013	-0.065	-0.030	-0.007	-0.083
	(0.005)	(0.022)	(0.005)	(0.017)	(0.005)	(0.025)	(0.016)	(0.005)	(0.049)
FS	-0.148	-0.142	-0.148	-0.108	-0.152	-0.155	-0.114	-0.152	-0.085
	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.005)	(0.001)	(0.008)
2SLS (ETI)	0.099	0.473	0.059	0.362	0.082	0.421	0.267	0.048	0.974
	(0.032)	(0.157)	(0.031)	(0.154)	(0.033)	(0.161)	(0.142)	(0.031)	(0.585)
N	25,886	2,902	22,984	2,504	23,382	2,375	1,977	21,007	527

Notes: The table shows reduced form, first stage, and 2SLS regression results estimating the ETI for middle income families based on the first base year. Robust standard errors in parentheses.

5.1.3 Robustness

Confounding wealth effects

One potential confounder is wealth effects, which could arise as families begin to pay for college expenses. Importantly, the income that enters into college aid calculations is earned one to two years prior to the year in which expenses are actually paid. The second panel of Table 4 marks with an "X" the years in which the treated and control cohorts will be paying for college expenses. In 2016, the control cohort begins paying for college, while the treated cohort is not yet paying for college in 2015 or in 2016. If families face liquidity constraints, this could induce a wealth effect such that the control cohort would begin to earn more income beginning in 2016. In turn, this would bias downward my estimated reduced form coefficient, as it would look like the treated cohort is reducing income relative to the control cohort.

Two results suggest this is not a significant confounder. First, if liquidity-induced wealth effects were an important confounder, this should have the greatest effect on the low income group, producing a coefficient for this group that is more negative than the middle or high income groups. This is not the case. In Figure 10, the point estimate for the low income group is closer to zero than for the middle income group, and it is statistically insignificant. Second, if liquidity-induced wealth effects were an important confounder, we should similarly expect to see a more negative reduced form coefficient for families with low assets. In fact, in Table 5 we see the opposite: the estimated effect is larger in magnitude for families with high assets.

Enrollment sample and additional years

As discussed in Section 4.1, my main enrollment sample includes all students enrolled at a public four-year college in California or at a private four-year college anywhere in the US. I additionally define an enrollment sample that only includes students enrolled at a public four-year college in California, as aid at these colleges more closely tracks the EFC formula. In this subsample, my measure of the marginal implicit tax rate from aid is likely to be more accurate, leading to more accurate estimates of the first stage effect on the log net-of-tax rate and of the ETI IV coefficient. It is worth noting that there is no reason to expect the estimates of the reduced form effect on income are any more or less accurate in either enrollment sample. The tradeoff for restricting to the UC and CSU subsample is a smaller sample size and lower statistical precision.

A second alternative sample I consider is to expand to include years after the introduction of prior-prior. The difference-in-differences approach I use above to estimate the ETI in the first year of means testing relies on the assumption that families in the treated 2017-18 cohort treated income earned in 2015 as though it would not affect aid, which is justified by the surprise announcement of the prior-prior policy on September 13, 2015. However, if families remain inattentive to the prior-prior policy shift even in years after it has been in place, I would be able to apply the same difference-in-differences design to later cohorts as well. In the online survey of parent perceptions of college aid, I include a question that asks which year of parent income is asked for on the FAFSA corresponding to the 2023-24 academic year. 74% of respondents reply that the 2023-24 FAFSA asks for income earned in 2022, while only 4% report the correct answer of 2021, suggesting the overwhelming majority of parents are not aware of the prior-prior policy and therefore still treat the income they will actually report on their first FAFSA for a new enrollment spell as though it would not affect aid. Based in this evidence, I expand the difference-in-differences design to also include the change in income from 2016 to 2017 for cohorts 2017-18 (control) and 2018-19 (treated), and the change in income from 2017 to 2018 for cohorts 2018-19 (control) and 2019-20 (treated). In this larger sample, I estimate the same difference-in-differences specifications in Equations (9) and (10) by baseline income bin while also controlling for the year of an observation. Because a given family can now appear with two observations – one treated and one control – I cluster standard errors at the family level.

Appendix A reports the results from the UC and CSU subsample, the expanded set of years, and the combination of the UC and CSU subsample using the expanded set of years. Results are similar across these alternative samples.

5.2 Income Response to Second Child Enrolling – High Income Families

I exploit a second source of variation in the college aid implicit tax to estimate the ETI for higher income families. Many families with income above $140k receive no financial aid with one child enrolled and as a result face no marginal phaseout of aid with income, but will begin receiving aid and facing a positive marginal implicit tax rate from aid when they have two children enrolled simultaneously.[17] I leverage the variation in implicit marginal tax rates due to enrolling a second child in an event study

[17] This is especially true at public four-year colleges. The income threshold for receiving aid with one child enrolled is generally higher at private four-year colleges.

design to estimate the ETI for families with income between \$140k and \$240k.

5.2.1 Empirical Strategy

Many families with income between \$140k and \$240k receive no financial aid with one child enrolled and therefore face no marginal phaseout with aid over income, but will receive aid with two children enrolled and in turn face a positive marginal implicit tax from aid. This is due to the EFC formula that underlies financial aid at most colleges, which divides a family's expected contribution toward college by the number of family members currently enrolled.[18]

Figure 11 demonstrates this feature of aid at the sample UC campus. The blue line in Figure 11 shows the same aid schedule over parent pre-tax income as in Figure 1. The red line in Figure 11 shows the total aid a family would receive with two members enrolled at the sample UC. At low incomes below \$40k, total aid is doubled. Beginning at incomes just above \$40k, total aid is phased out at the same rates.[19] Because total aid starts from a higher base level at low incomes and phases out at the same marginal rates, this produces the highlighted region wherein families receive no aid and face a zero marginal implicit tax rate from aid with one child enrolled, but begin to receive aid and face a positive marginal implicit tax rate when a second child enrolls. In the case of the sample UC, this region occurs for families with income from approximately \$150k to \$225k.

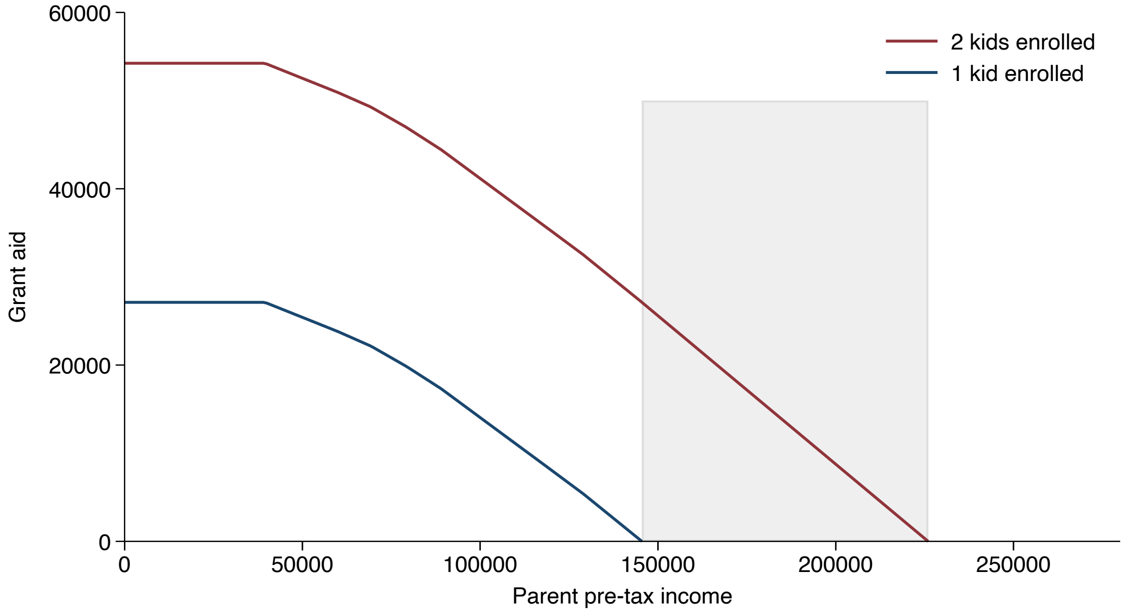
Figure 12 shows the marginal implicit tax rates on aid associated with the aid schedules for one or two kids enrolled in Figure 11. In the range of income from \$150k to \$225k, when a family moves from having one to two kids enrolled, their marginal implicit tax rate from aid jumps from zero to over 30%.

I estimate the ETI for the high income range (\$140k to \$240k) using an event study design around the first year in which a family's income will determine aid for two children. Table 6 illustrates the comparisons in my design. I compare families with two enrollment patterns: 0-1-1-2 and 0-1-2-2. I will refer to these, respectively, as the 112 group and the 122 group; they differ in whether the spacing between the two children's enrollment is one or two years. The first panel of Table 6 simply shows the enrollment patterns aligned based on the year in which the first child enrolls. The second panel shows whether income in each year is used to determine aid for one or two kids, which affects the marginal implicit tax rate from aid the family faces. My full event study specification makes two types of comparisons. The blue arrow labeled "A" highlights the first comparison, which compares the change in income from the

[18] Under the FAFSA Simplification Act, EFC will be replaced by the Student Aid Index (SAI) beginning in the 2024-25 academic year. The SAI will no longer have the feature of being divided by the number of family members enrolled, thus removing this source of variation to study the ETI for higher income families.

[19] Because EFC is divided by number of family members enrolled, the implicit marginal tax rate from aid *per child* is cut in half in this range when a family enrolls a second child. The total marginal implicit tax rate is unchanged as it is cut in half on a per child basis when the second child enrolls, but the family's total marginal phaseout rate is now the sum across both children.

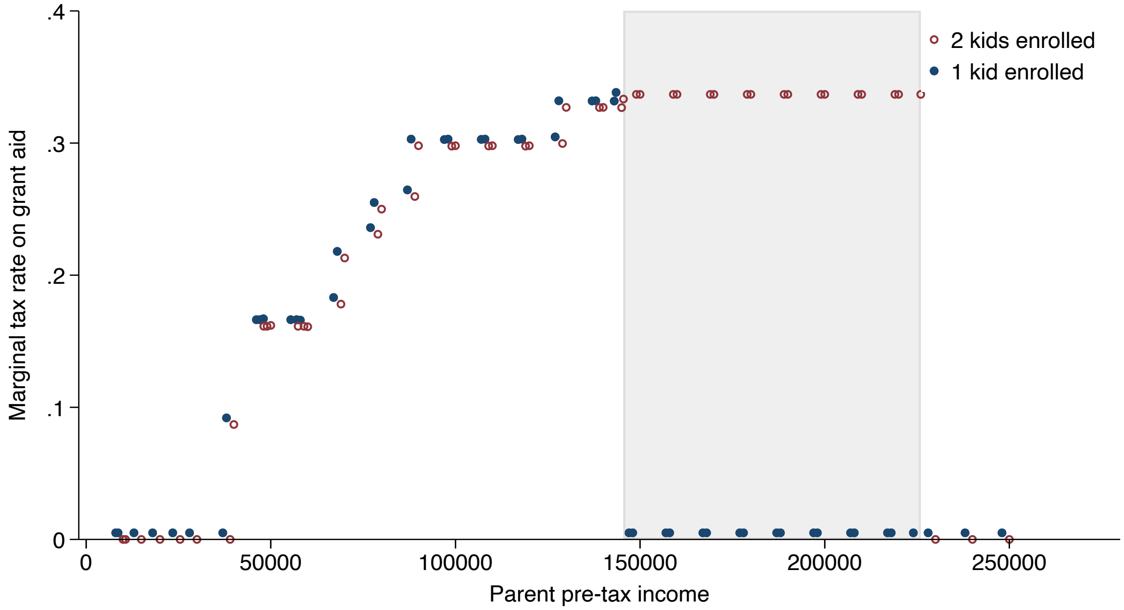
Figure 11: Example Grant Aid at Sample UC for 1 vs. 2 Kids Enrolled



Notes: The bottom line shows the same grant aid schedule over parent pre-tax income at the Sample UC as in Figure 1. The top line shows the total aid a family would receive with two children both enrolled at the Sample UC based on parent pre-tax income. In the highlighted region from approximately \$150k to \$225k, families receive no aid and face a zero marginal implicit tax from aid with one child enrolled, but with two children enrolled they receive aid and they face a high marginal implicit tax.

first to the second base year across the two groups. For the 112 group, income in both years is subject to the one kid aid schedule; for the 122 group, income is subject to the one kid aid schedule in the first year, but is subject to the two kids aid schedule in the second year. In this comparison, the 122 group is newly "treated" by the two kids implicit tax schedule, while the 112 group serves as a control. The red arrow labeled "B" highlights the second comparison, which compares the change in income from the second to the third base year across the two groups. For the 112 group, income is subject to the one kid aid schedule in the first year, but is subject to the two kids aid schedule in the second year; for the 122 group, income in both years is subject to the two kids aid schedule. In this comparison, the 112 group is newly "treated" by the two kids implicit tax schedule, while the 122 group serves as a control. I combine the two sources of variation to estimate the reduced form response of income to the two kids aid schedule, the first stage effect on the marginal implicit tax rate, and finally the ETI. In all regressions, I include data from all years available (2010-2021), except I omit observations that would measure changes in income from the 2016-17 to the 2017-18 school years. This is because, due to the prior-prior policy shift described above, both 2016-17 and 2017-18 school years used income earned in 2015 to determine aid. I only allow each family to appear at most once with a 112 or 122 pattern; if a family displays either of the two enrollment patterns at two separate times, I only use the first instance. This means that each family contributes at most two observations to the below regressions:

Figure 12: Example Aid MTR at Sample UC for 1 vs. 2 Kids Enrolled



Notes: The figure plots the marginal implicit tax rates for families with one or two children enrolled, which correspond to the magnitude of the slopes in Figure 11.

one comparison A observation, and one comparison B observation. In all below regressions, I cluster standard errors at the family level to account for families with two observations.

The third panel of Table 6 addresses the timing of potential wealth effects due to paying for college, showing the number of children whose tuition is paid in each year. Because aid is based on income earned prior to enrollment, both groups in comparison A are not paying any college expenses in the first income base year, and they are paying college expenses for one child in the second base year. In the B comparison, the treated 112 group is paying college expenses for one child in both base years, while the control 122 group is paying college expenses for one child in the first base year and for two children in the second base year. If there was an important wealth effect at the start of paying for two children in college, this could bias in favor of finding a relative reduction of income in the treated group in comparison B, as the control group would be increasing income to pay for college. If this was the case, estimated effects would be larger among families with low assets, and smaller among families with high assets. Similar to the previous section, estimated effects shown below are generally greater among families with high assets, suggesting there is not an important wealth effect biasing in favor of finding a relative reduction of income in the treated group.

The reduced form event study regression estimating the response of income to the two kid implicit tax

Table 6: Event Study Comparison

Years relative to first child enrolled	**-1**		**0**		**1**	**2**
# kids enrolled						
1-1-2	0		1		1	2
1-2-2	0		1		2	2
# kids aid schedule (substitution effect)						
1-1-2	1	$\xrightarrow{A}$	1	$\xrightarrow{B}$	2	-
1-2-2	1		2		2	-
# kids tuition (wealth effect)						
1-1-2	0		1		1	2
1-2-2	0		1		2	2

Notes: This table details the event study design used to estimate the ETI for high income families based on changes between having one or two kids enrolled. The top panel describes the two enrollment patterns being compared. Both patterns switch from one to two kids enrolled, the only difference being whether there is a one or two year gap between the first and second child enrolling. The middle panel shows whether each year of income is used to determine aid for one or two kids. The "A" comparison uses the first change in income, when the 1-2-2 pattern is being newly exposed to the 2 kids aid schedule but the 1-1-2 pattern faces no change in incentives. The "B" comparison uses the second change in income, when the 1-1-2 pattern is being newly exposed to the 2 kids aid schedule but the 1-2-2 pattern faces no change in incentives. The bottom panel details the potential timing of liquidity-induced wealth effects based on when college costs are paid. In the "A" comparison, the two patterns face the same change in costs. In the "B" comparison, the 1-2-2 pattern begins paying for two children while the 1-1-2 pattern continues paying for one child. It is possible that this could induce a confounding wealth effect. I revisit this in Section 5.2.3.

schedule is as follows:

$$\ln(TI_{i,t}) - \ln(TI_{i,t-1}) = \alpha^{RF}_{c(i)} + \beta^{RF} treated_{i,t} + \gamma^{RF} pattern_i + \xi^{RF} eventyear_{i,t} + \epsilon_{i,t} \quad (12)$$

where t is years relative to the year in which the first child enrolls as labeled in Table 6; t is fixed to 0 among A comparison observations and is fixed to 1 among B comparison observations to isolate the relevant comparison years; $c(i)$ is the cohort of family i, which is the year of the first child's enrollment; $treated_{i,t}$ is an indicator for income being newly subject to the two kid implicit tax schedule, which occurs in the second base year (event year 0 in Table 6) for the 122 group and in the third base year (event year 1 in Table 6) for the 112 group; $pattern_i$ is an indicator to control for being in the 112 group or the 122 group; and $eventyear_{i,t}$ is a control for whether t equals 0 (coming from the A comparison) or t equals 1 (coming from the B comparison). This design implicitly compares the change in log income between two types of families: first, a treated family whose income is newly subject to the two kids implicit tax schedule; and second, a control family whose income is subject to either the one kid or the two kids implicit tax schedule in both years. The implicit comparison isolates families who both sent their first child to college beginning in the same year and the comparison observations come from the same year within the enrollment spell. The regression further controls for a fixed effect corresponding to a 112 or a 122 enrollment pattern.

I then estimate the first stage effect of the two kid implicit tax schedule on the (simulated) log net-of-tax rate as:

$$\ln(1-\hat{\tau}_{i,t}) \;-\; \ln(1-\tau_{i,t-1}) \;=\; \alpha^{FS}_{c(i)} \;+\; \beta^{FS} treated_{i,t} \;+\; \gamma^{FS} pattern_i \;+\; \xi^{FS} eventyear_{i,t} \;+\; \epsilon_{i,t} \quad (13)$$

where $\tau_{i,t-1}$ is the actual marginal implicit tax rate for family i in year $t-1$, and $\hat{\tau}_{i,t}$ is the simulated marginal implicit tax rate. The simulated rate $\hat{\tau}_{i,t}$ holds all aid inputs fixed from year $t-1$, except for using the number of kids enrolled in t. The left hand side of the regression therefore measures the simulated change in marginal implicit tax rate, which is the change that would occur if the family kept all aid inputs fixed except for (potentially) changing the number of kids enrolled.

I then estimate the ETI using IV:

$$\beta^{ETI} \;=\; \frac{\beta^{RF}}{\beta^{FS}} \quad (14)$$

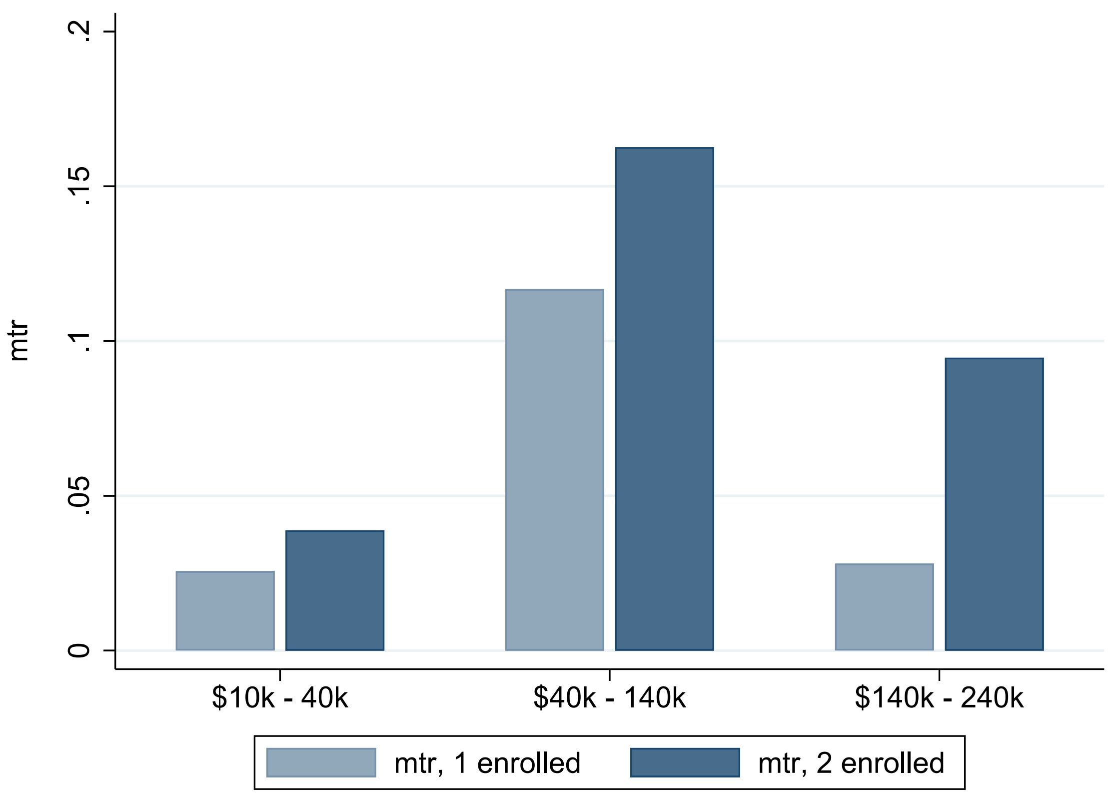
An important limitation in the FAFSA data should be mentioned. In the academic years 2010-11 through 2013-14, a small number of fields necessary to the EFC calculation are missing for most observations, meaning the marginal implicit tax rate from aid cannot be calculated. However, these observations still record information on parent income. To maximize precision using the available data, I estimate the reduced form in Equation (12) using all years of FAFSA data, and I estimate the first stage in Equation (13) using all observations with sufficient information to measure EFC and estimate the marginal implicit tax rate from aid. The sample used to estimate the first stage is generally smaller than the sample used to estimate the reduced form. Validity of the first stage and the ETI estimates rely on an assumption that the average marginal implicit tax rate from aid is nearly constant within income range over years, which is likely the case as aid schedules do not change dramatically from one year to the next. I use a bootstrap procedure to compute standard errors on the ETI.

As noted in Section 5.1.3, evidence from the online survey supports the notion that families are still mostly unaware of prior-prior: 74% of respondents to the online survey answered that the 2023-24 FAFSA asks information about income earned in 2022, while only 4% report the correct answer of 2021. Following this evidence, for observations after 2017-18 (the year prior-prior was introduced), I continue to rely on income observations with the same timing relative to enrollment as shown in Table 6. For example, if a family's first enrollment occurs in 2018-19, I use the change in income from 2017 to 2018 for this family's comparison A observation, even though the first two years of income the family would report on their FAFSA are 2016 and 2017. In this way, comparison A observations measure the change in income between the first two years a family would have expected their income was used to determine aid, as opposed to the first two years of income actually used to determine aid; similarly, comparison B observations measure the change in income between the second and third years a family would have expected their income was used to determine aid, as opposed to the second and third years of income actually used to determine aid.

5.2.2 Results

To begin, Figure 13 shows the average marginal implicit tax rate from aid in each of the three income bins separately for a family with one child enrolled and for a family with two children enrolled. The largest increase in the marginal implicit tax rate occurs for the high income group, who face an average jump in their marginal implicit tax rate of 7pp when enrolling a second child.

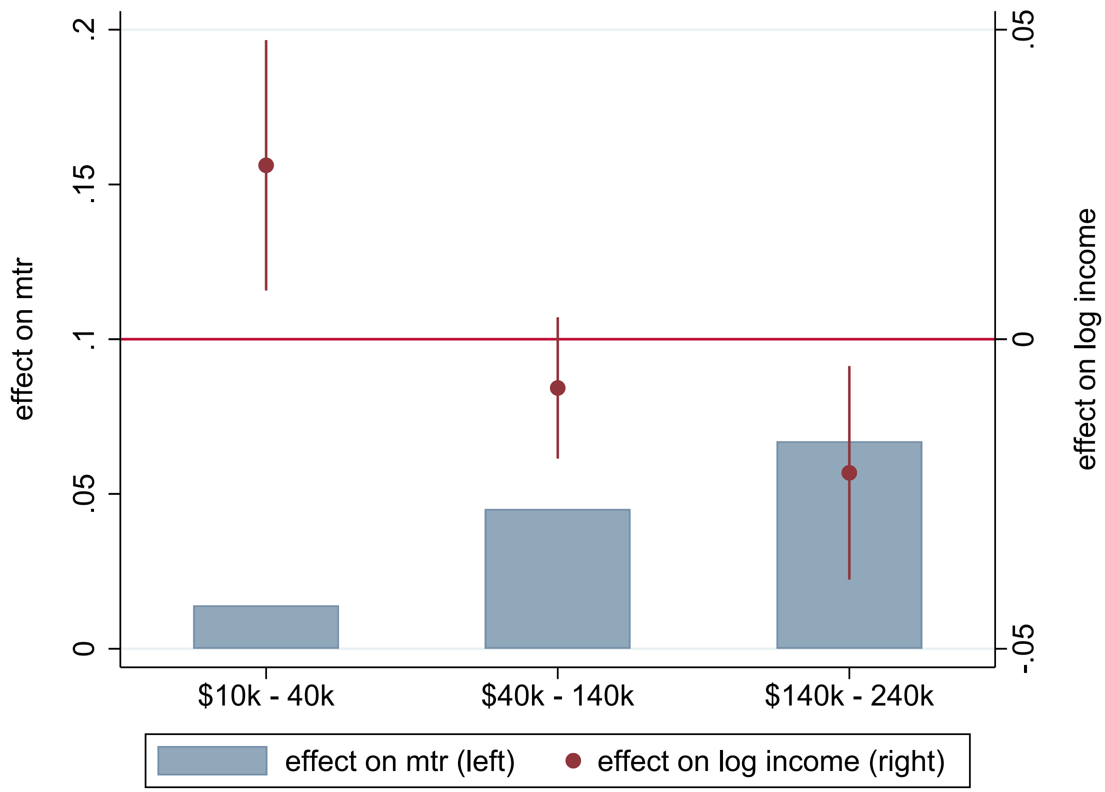
Figure 13: MTR for 1 vs. 2 Kids Enrolled



Notes: This figure shows the average marginal implicit tax rate from aid for families with one or two kids enrolled, separately by parent income.

Figure 14 shows the effect of the two kids aid schedule relative to the one kid aid schedule on log income alongside the effect on the marginal implicit tax rate. The estimated reduced form effect of being exposed to the two kids aid schedule is a reduction of income of 2.2% among the high income group. It is worth observing that the low income group increases income by nearly 3% when being newly exposed to the two kids aid schedule. It is possible this is an anticipatory wealth effect. Each treated observation comes from a family that will enroll their second child in the subsequent year. If low income families are liquidity constrained and begin to increase income to pay for college expenses one year before the second child enrolls, this would produce an effect like that seen in Figure 14.

Figure 14: Effect on MTR and Income for 1 → 2 Enrolled



Notes: Separately by baseline income, the figure shows the first stage effect of the two kids aid schedule on the simulated marginal tax rate from aid as bars (left axis) and the effect on log income in dots (right axis) with 95% confidence intervals clustered at the family level.

Reduced form, first stage, and ETI estimates for the high income group are reported in Table 7. The ETI for the high income group overall is 0.28. Further splits based on whether a family has a high non-labor share of income or high assets are consistent with the results of Section 5.1 in which these families are more responsive. However, it is difficult to draw firm conclusions regarding heterogeneous effects due to the wide standard errors.

5.2.3 Robustness

Confounding wealth effects

Table 7: Elasticity for $1 \rightarrow 2$ Enrolled

		By non-labor income share		By assets	
	Full sample	High	Low	High	Low
RF	-0.022	-0.024	-0.022	-0.033	-0.017
	(0.009)	(0.035)	(0.009)	(0.016)	(0.010)
FS	-0.078	-0.075	-0.079	-0.056	-0.089
	(0.003)	(0.009)	(0.004)	(0.005)	(0.004)
2SLS (ETI)	0.276	0.320	0.277	0.592	0.188
	(0.118)	(0.491)	(0.112)	(0.280)	(0.115)
N: RF	7,513	939	6,574	2,518	4,995
N: FS	4,255	478	3,777	1,456	2,799

Notes: The table shows reduced form, first stage, and 2SLS regression results estimating the ETI for high income families based on changing from one to two kids enrolled. Standard errors are clustered at the family level.

As in Section 5.1, a potential confounder is liquidity-induced wealth effects. In particular, among comparison B observations, the control group is beginning to pay college expenses for two kids, which could result in a liquidity-induced increase in income to help pay for college expenses among the control group, which in turn would bias my results toward finding a reduction of income among treated observations. Three reasons suggest this is unlikely to be an important confounder. First, the high income group – with income from \$140k to \$240k – is less likely to face liquidity constraints. Second, if liquidity constraints were biasing my results toward finding a reduction of income in the treated group, we should see a larger reduction of income in the treated group for low income families. In fact we see a relative increase of income in the treated group for low income families. Finally, the estimated ETI in Table 7 is higher for families with high assets, again the opposite of what we would expect to see if liquidity constraints were an important confounder.

Enrollment sample

Similar to Section 5.1, I re-estimate the above effects using the subsample of students enrolled only at a public four-year college in California, where my measure of the marginal implicit tax rate is likely to be more accurate. I report these results in Appendix B. Estimates generally do not change in the UC and CSU subsample, with the exception of a much higher point estimate for the ETI among families with a high share of non-labor income; however, the sample size for this estimate is very small and the standard error is quite wide.

6 Identifying the Structural Elasticity and the Impact of Misperception on Deadweight Loss with an Online Survey

6.1 Structural Elasticity

I begin with estimates of the structural elasticity. To compute these, I combine estimates of $\beta^{ETI}(X_i)$ from FAFSA data with estimates of $\frac{E[\ln(1-\tau_i)\mid X_i]}{E[\ln(1-\tilde{\tau}_i)\mid X_i]}$ from the online survey and plug these into Equation (4). Throughout this section, I assume $\frac{E[\ln(1-\tau_i)\mid X_i)]}{E[\ln(1-\tilde{\tau}_i)\mid X_i]}$ does not vary with X_i, so in practice I use estimates of the unconditional quantity $\frac{E[\ln(1-\tau_i)]}{E[\ln(1-\tilde{\tau}_i)]}$.

Table 8 lists the estimated reduced form elasticity β^{ETI} and the structural elasticity e for several subgroups among the middle income group ($40k to $140k).

Table 8: Reduced Form and Structural Elasticities

		By non-labor income share and assets			
	Full Sample	High, low	Low, high	Low, low	High, high
Reduced form elasticity β^{ETI}	0.099	0.421	0.267	0.048	0.974
	(0.032)	(0.161)	(0.142)	(0.031)	(0.585)
Structural elasticity e	0.089	0.378	0.240	0.043	0.875
	(.029)	(.146)	(.128)	(.028)	(.527)

Notes: This table reports the reduced form elasticity estimates from Section 5.1 alongside estimates of the corresponding structural elasticity. To compute standard errors for the structural elasticity, I use the fact that for two independent random variables X and Y, $Var(XY) = Var(X)Var(Y) + Var(X)E(Y)^2 + Var(Y)E(X)^2$. Here, X is my estimator of the reduced form ETI in the FAFSA data, and Y is my estimator in the survey data of $\frac{E[\ln(1-\tau_i)]}{E[\ln(1-\tilde{\tau}_i)]}$. I estimate $SE(e) = \sqrt{Var(XY)}$ by plugging in preceding point estimates and standard errors to the expression for $Var(XY)$.

In the survey data, I estimate $\frac{E[\ln(1-\tau_i)]}{E[\ln(1-\tilde{\tau}_i)]} = 0.90$, reflecting that on average parents slightly overestimate their log not-of-tax rate in magnitude. As a result, the structural elasticity is 10% lower than the reduced form elasticity.

6.2 Impact of Misperception on Deadweight Loss

6.2.1 Empirical Strategy

Section 3.3 derives an expression for DWL under correct perceptions or under misperception, along with the impact on DWL due to misperception. The impact of misperception on DWL can be summarized by the average square of the misperception parameter, $E[\theta_i^2]$, which can be decomposed into a bias channel $(E[\theta_i]^2 - 1)$ and a variance channel $Var(\theta_i)$. Here, I estimate DWL under correct perceptions and under misperception, the impact on DWL due to misperception, and the contributions from the bias and variance channels. First, I describe an instrumenting procedure I use to estimate the impact of misperception on DWL and the contribution from the variance channel, which leverages the instrument τ_i^{4575} to separate true variation in perceived implicit tax rates from noise.

To motivate the instrument, consider first a simple approach. In the survey data, I have a direct measure of θ_i for each survey respondent with income below \$110k. With this, one could directly compute the sample analogs of the proportional increase in DWL due to misperception $(E[\theta_i^2]-1)$, the contribution from bias $(E[\theta_i]^2 - 1)$, and the contribution from variance $Var(\theta_i)$ using sample means and variances. However, suppose each respondent's θ_i is measured with noise that is mean zero but has positive variance. Then the simple estimates of the increase in DWL due to misperception and the contribution from variance will be overestimated because they will incorporate the variance of the noise.

To solve this problem, I leverage the instrument $\tilde{\tau}_i^{4575}$, which measures the respondent's guess of the marginal implicit tax rate from aid over the range of income from \$45k to \$75k. The approach is similar to the procedure introduced in Taubinsky and Rees-Jones (2018) to measure variation in individual under-reaction to sales taxes. The intuition is to use the instrument $\tilde{\tau}_i^{4575}$ to classify respondents into groups indicating whether they generally believe aid phases out more or less quickly over income, and then use only the variation in θ_i that occurs *across* these bins to estimate the above variance parameters. Specifically, I classify respondents into four bins corresponding to quartiles of $\tilde{\tau}_i^{4575}$. I then assign each respondent the average θ_i within their bin, which is the instrumented θ_i. Finally, I compute the direct sample analogs of the proportional increase in DWL due to misperception $(E[\theta_i^2]-1)$, the contribution from bias $(E[\theta_i]^2 - 1)$, and the contribution from variance $Var(\theta_i)$ using sample means and variances of the instrumented θ_i. This procedure isolates only across bin variation in θ_i under the assumption that this variation is due to true underlying variation in respondent perceptions rather than noise. Importantly, the approach will produce an underestimate of the proportional increase in DWL due to misperception and the contribution from variance to the extent that there is true within bin variation in θ_i.[20]

[20] This last point is due to the Law of Total Variance, which states that the variance of a random variable Y can be expressed as the sum of two components: (i) the average conditional variance of Y given another random variable X; and (ii) the variance of the conditional mean of Y given X. The instrument approach outlined here isolates the second component, and will therefore produce an underestimate of variance with the discrepancy equal to the average conditional variance of θ_i within quartiles of $\tilde{\tau}_i^{4575}$.

6.2.2 Results

Table 9 summarizes the DWL estimates among the middle income group ($40k to $140k) who are primarily subject to positive marginal implicit tax rates from college aid. The first column reports average DWL per family per year in dollars. The second column multiplies this by the total number of California resident families with a dependent student enrolled at a California public four-year college in 2020 (134,642) who file a FAFSA for that year, to measure the total DWL per year among these families. The third column scales average DWL per family per year by average annual aid ($11,408.76) to report DWL as a percent of aid. Under the counterfactual in which all families hold correct perceptions of the college aid implicit tax schedule, I estimate the efficiency cost of means-testing would be $125.23 per family per year of enrollment on average. This amounts to $16.9 million per year and 1.1% of total aid. Misperception more than doubles the efficiency cost of means-testing in college aid. Because parents do not hold correct perceptions of the college aid implicit tax schedule, average DWL per family per year is $264.91. This amounts to $35.7 million per year and 2.3% of total aid. In total, misperception increases DWL by $139.67 per family per year, which is $18.8 million per year and 1.2% of total aid.

Table 9: Deadweight Loss from Means-Testing College Aid With and Without Misperception

	Average DWL per family-year	Average DWL per year	DWL as percent of aid
Without misperception	$125.23	$16.9 million	1.1%
With misperception	$264.91	$35.7 million	2.3%
Difference	$139.67	$18.8 million	1.2%

Notes: This table reports estimates of DWL based on Equation (7). The first row isolates the "correct perceptions" portion of Equation (7). The second row also includes the contribution from misperception, and the third row equals the second minus the first.

Table 10 reports the proportional increase in DWL due to misperception along with contributions from the bias and variance channels. Misperception increases DWL by 112% relative to the counterfactual in which all families hold correct perceptions of the college aid implicit tax schedule. Because misperception is not large on average, the contribution from the bias channel is near zero and insignificant. The variance channel alone increases DWL by 106%, accounting for effectively all of the increase in DWL due to misperception. This result is similar to that of Rees-Jones and Taubinsky (2018), who find that heterogeneity in salience of a sales tax across individuals increases DWL by over 200%.

The results in Table 9 and Table 10 are significant for a few reasons. First, I find that means-testing

Table 10: Impact of Misperception Bias and Variance Channels on Deadweight Loss

Proportional increase in DWL due to misperception	**Contribution from**: Bias	Variance
$\hat{E}[\theta_i^2] - 1$	$\hat{E}[\theta_i]^2 - 1$	$\hat{Var}(\theta_i)$
1.12	0.05	1.06
(0.26)	(0.19)	(0.22)

Notes: This table decomposes the impact of misperception on DWL into its bias and variance components, as in Equation (8). Bootstrap standard errors based on 1,000 resamples in parentheses.

in college aid creates an efficiency cost that should be accounted for in assessments of the optimal aid schedule, which weigh the tradeoff between equity and efficiency inherent in means-testing. Second, I find that the efficiency cost of means-testing in college aid is small relative to the amount of aid received by families subject to the strongest aid incentives. In total, the efficiency cost of means-testing in college aid accounts for 2.3% of total aid received by families in the middle income range ($40k to $140k). Third, I find that DWL is increased considerably – by 112% – in the college aid setting due to misperception. The total increase in DWL due to misperception is equal to $18.8 million per year among middle income families in California alone. To my knowledge, this is the first result to directly estimate the impact of misperception on DWL due to a tax, whether implicit or explicit. Finally, in my setting, all of the increase in DWL due to misperception comes through the variance channel. Even though the college aid implicit tax schedule is highly complex and difficult to learn, parents' perceptions of their marginal implicit tax rate from aid are not far from the truth on average. However, there is significant variation in perceptions across individuals. As outlined in Section 3.3, this high degree of variability in misperception across individuals creates substantial DWL because DWL rises with the square of the tax rate, and misperception can be viewed as an additional tax levied on top of the true tax rate. This finding holds important implications for the design of and information policies around college aid, as well as broader implications for the wide array of complex tax schedules for which the impact of misperception on DWL has not yet been assessed.

7 Discussion

7.1 The Efficiency Cost of Means Testing in College Aid

College financial aid creates large marginal implicit tax rates on parent income for millions of middle income families each year, and this means testing produces an efficiency cost to the extent that families temporarily reduce income in the years that affect their college aid. Accounting for misperception, I find that the structural ETI for parent income with respect to the college aid implicit tax is 0.09 among middle income families who face the highest implicit tax rates from aid. Because families reduce parent income in the years that affect college aid, I estimate an efficiency cost equal to \$264.91 per family per year, which amounts to \$35.7 million per year among California families with a child enrolled at a California public four-year college or a private four-year college in any state. This represents 2.3% of total aid among this population.

Earlier literature observed that means testing in college aid creates large implicit incentives for families to reduce income and assets as these reductions are offset by increased aid, expressing concern that such changes in behavior might produce a large efficiency cost (Case and McPherson, 1986; Edlin, 1993; Fedlstein, 1995; Dick and Edlin, 1997). My results suggest that the efficiency cost of means testing college aid against parent income is not large relative to the size of the program, despite the large incentives created by means testing.

My estimated elasticity and corresponding efficiency cost are consistent with estimates in other settings, most notably estimates of the Frisch intertemporal elasticity of labor supply in "tax holiday" settings. Tax holidays occur when income is not subject to a federal income tax temporarily as a country adjusts its income tax system, producing an incentive to increase income in tax-free years motivated by intertemporal substitution. Recent estimates of the Frisch elasticity of labor supply in tax holidays settings include elasticities of 0.017 in Argentina (Tortarolo et al., 2020) and 0.025 in Switzerland (Martínez et al., 2021). Means testing college financial aid against parent income produces an "anti tax holiday" in which income is termporarily subject to a higher marginal tax rate. My estimate of a reduced form ETI with respect to the college aid implicit tax of 0.10 among middle income families is somewhat higher than tax holiday estimates of the Frisch labor supply elasticity. The discrepancy might be due to my income measure including labor and non-labor sources, as non-labor income sources are typically more elastic.

Existing literatures find evidence that labor adjustment fictions (Pencavel, 1986; Blundell and Macurdy, 1999) and information frictions (Chetty et al., 2013; Chetty and Saez, 2013) often lower reduced form elasticities of income and labor supply with respect to variation in the effective wage. In a recent paper, Kostøl and Myhre (2021) study the relative impact of information frictions and other frictions such as labor adjustment costs on labor supply response to welfare program incentives in Norway. They estimate a reduced from elasticity of 0.06 and a "frictionless" elasticity of 0.30, with information frictions accounting for 30 percent of this gap. Other frictions such as labor adjustment costs account for the remaining 70 percent.

In the setting of college aid, I find that misperception has little impact on the reduced form elasticity, if anything *increasing* the reduced form elasticity slightly from 0.09 to 0.10. In the online survey I administered to parents, I find suggestive evidence supporting the hypothesis that labor adjustment frictions lower the ETI and thereby the efficiency cost of means testing college aid against parent income. In the survey, parents are asked to what extent they agree with the following statements: "I have given considerable thought to how I can maximize my child's financial aid", "It is fair to reduce income and receive more financial aid", and "If we wanted to, our family could reduce income for a few years". Respectively, these questions offer a simple assessment of the scope for salience, fairness considerations, or labor adjustment costs to lower the reduced form ETI. Table 11 shows the proportion of respondents selecting each answer for each question, with possible answers ranging from "Strongly disagree" to "Strongly agree" on a five-point scale. 61% of respondents either somewhat disagree or strongly disagree with having the ability to temporarily reduce income. In contrast, 38% of respondents somewhat disagree or strongly disagree with having given considerable thought to maximizing aid, and 36% somewhat disagree or strongly disagree with the statement that reducing income and receiving more aid is fair. While suggestive, this evidence points toward labor adjustment frictions being one potentially important factor lowering the reduced form ETI.

Table 11: Potential Mechanisms Shaping Reduced Form ETI

		Proportion of respondents selecting each answer				
Mechanism	Question text	Strongly disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Strongly agree
Salience	I have given considerable thought to how I can maximize my child's financial aid	0.14	0.24	0.19	0.29	0.15
Fairness	It is fair to reduce income and receive more financial aid	0.17	0.19	0.31	0.22	0.11
Labor	If we wanted to, our family could reduce income for a few years	0.36	0.25	0.13	0.19	0.07
N	1,886					

Notes: This table lists the proportion of survey respondents choosing each response ranging from "Strongly disagree" to "Strongly agree" for the three questions listed above.

7.2 Misperception and the Efficiency Cost of Means Testing

A priori, it is unclear whether misperception increases, decreases, or has no net effect on the efficiency cost of taxes in various settings. Recent papers find evidence that individuals often rely on an "ironing" heuristic to understand a nonlinear price or tax schedule, in which the marginal price or tax rate is replaced with the average.[21] In the context of a progressive tax schedule, ironers will underestimate the marginal tax rate they face, which would lower the reduced form ETI and decrease the efficiency cost of the tax. However, it is not clear whether individuals consistently rely on an ironing heuristic to understand various tax schedules, or whether richer forms of misperception might exist in the setting

[21] See Ito (2014) for the case of electricity prices and Rees-Jones and Taubinsky (2020) for the case of the federal income tax in the US.

of other tax schedules. Moreover, previous research does not account for the impact of heterogeneity in misperception on the efficiency cost of a tax.

The model I outline in Section 3.3 makes clear that misperception affects DWL from a tax through two channels: a bias channel measuring the average misperception; and a variance channel measuring heterogeneity of misperceptions across individuals. This result further emphasizes that the impact of misperception on DWL is a priori ambiguous; misperception can increase, decrease, or have no net impact on DWL depending on both the average misperception and the variance of misperceptions.

In the college aid setting, I find that parents exhibit little bias in perception on average, but that there is substantial variability of misperception across individuals. I estimate that this heterogeneity in misperception doubles the efficiency cost of means testing in college aid. As explained in Section 6.2, my estimates reflect a lower bound. My results underscore that information frictions do not always lower the efficiency cost of a tax, but can significantly increase DWL instead. My results also highlight the central role of accounting for the variance of misperception when assessing the impact of misperception on DWL. Both the theoretical and empirical results relating to the impact of misperception on the efficiency cost of a tax are novel, and they are closely related to similar results in Taubinsky and Rees-Jones (2018) and Morrison and Taubinsky (2023) finding that heterogeneity in salience of a sales tax considerably increases the efficiency cost of the tax. My results provide robust motivation for future research to assess the impact of misperception on the efficiency cost of taxes in various settings while outlining a concrete empirical strategy to do so, and they emphasize that such evaluations must account for heterogeneity in misperception.

I estimate that misperception increases the efficiency cost of means testing in college aid by $18.8 million per year among middle income families in California alone. This suggests that an information policy to better inform families of the college aid schedule over parent income could be highly cost effective, especially if implemented nationally.[22]

8 Conclusion

In this paper, I produce the first estimates of the elasticity of taxable income (ETI) with respect to the implicit tax on parent income in college financial aid, and I identify the extent to which misperception impacts the efficiency cost of means-testing in college aid. Using administrative FAFSA records and a difference-in-differences design around the first year in which income is expected to affect aid, I estimate an ETI of 0.10 among middle income families with income between $40k and $140k.

[22] This is without accounting for the positive impact that such a policy might have on college enrollment among students from lower income families as documented in previous work (e.g. Bettinger et al., 2012; Hoxby and Turner, 2015; Dynarski et al., 2021).

The ETI is larger among families with flexible non-labor income (ETI=0.47) and among families with high assets (ETI=0.36). In a second difference-in-differences design around enrolling a second child in college, I estimate an ETI of 0.28 for high income familes with income between \$140k and \$240k. I then conduct an online survey to directly measure parents' perceptions of the marginal implicit tax rate from aid that they face. I use the survey results to identify the structural ETI with respect to the perceived tax and the impact of misperception on DWL. I estimate a structural ETI that only differs from the reduced form ETI by 10%, consistent with the fact that respondents report a perceived marginal implicit tax rate that is close to the true value on average. I show theoretically that the impact of mispercepton on the efficiency cost of a tax comes through two channels: bias (misperception on average) and variance (heterogeneous misperception). Accounting for misperception, I estimate that the efficiency cost of means testing in college aid for middle income families equals 2.3% of total aid. Misperception increases the efficiency cost by \$18.8 million per year among middle income families in California alone. Effectively all of this increase is due to the high variance of misperceptions.

To my knowledge, this is the first paper to use survey data to directly estimate the impact of misperception on the efficiency cost of a tax, which leads to many exciting avenues for future research. The methods in this paper can be applied in various other settings with complex price or tax schedules to identify the contribution of misperception to deadweight loss, both through bias and variance channels. Additionally of importance is to extend the model in this paper to allow for heterogeneous elasticities and to further allow for correlation between an individual's elasticity and their misperception. This model extension is likely to produce further rich insights into the role mispeception plays in shaping the efficiency cost of taxation.

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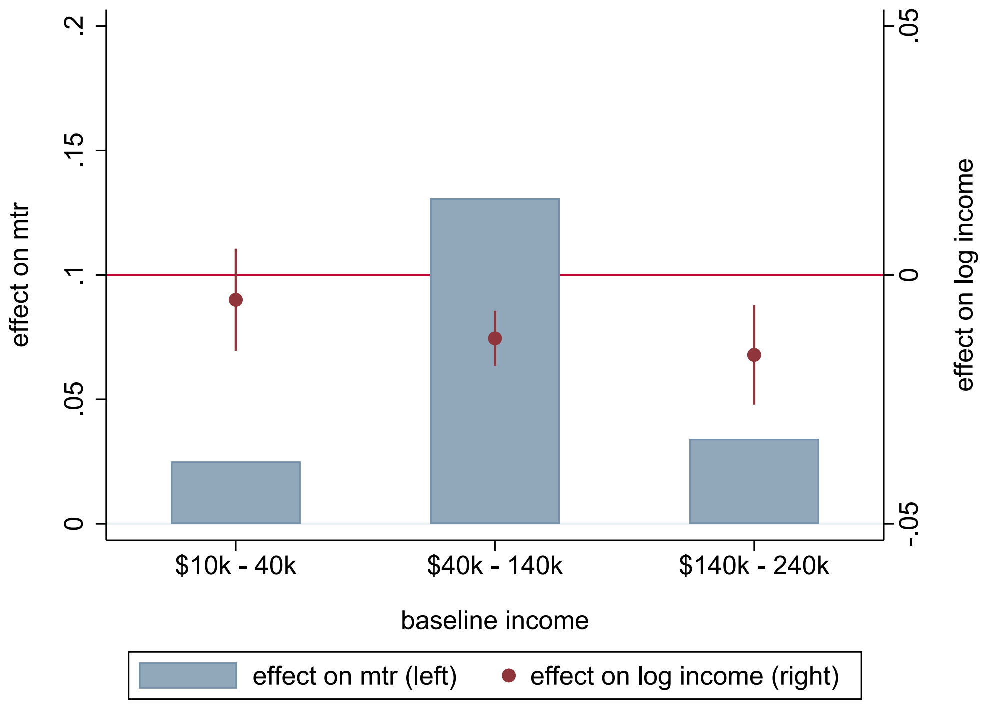
Appendix A: Estimates of the Reduced Form ETI in the First Year of Means Testing for Middle Income Families, using UC & CSU Enrollment Sample and Additional Years

Figure 15: First Base Year Effect on MTR and Income
Main Enrollment Sample; Expanded Years



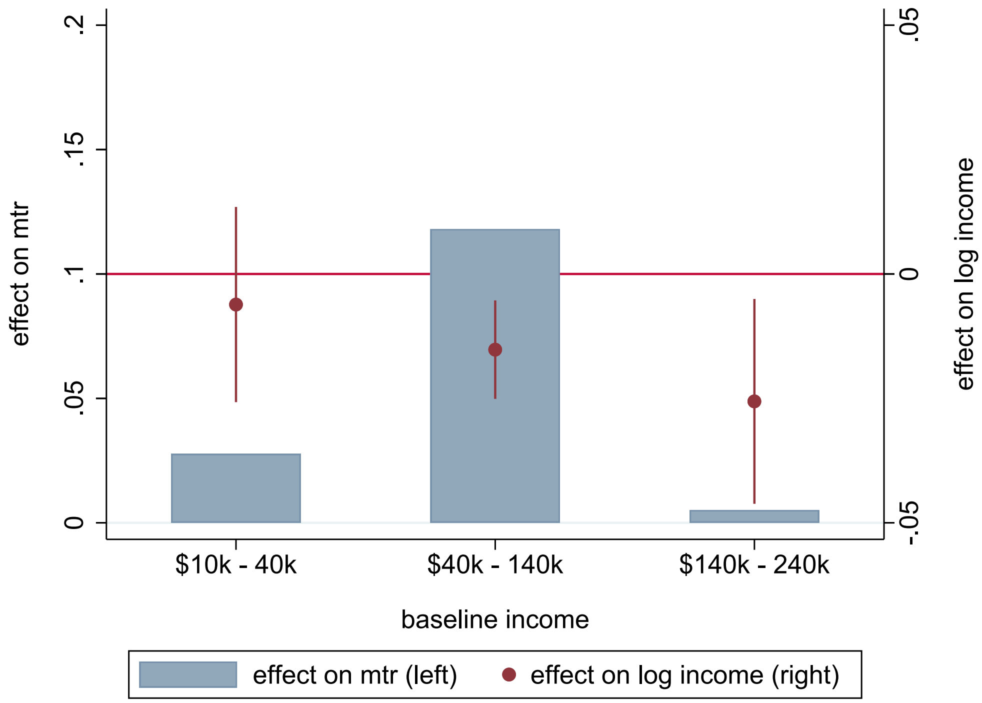
Notes: Separately by baseline income, the figure shows the first stage effect of the first base year on the simulated marginal tax rate from aid as bars (left axis) and the effect on log income in dots (right axis) with 95% confidence intervals clustered at the family level.

Table 12: First Base Year Elasticity of Taxable Income – Middle Income Families
Main Enrollment Sample; Expanded Years

		By non-labor income share		By assets		By non-labor income share and assets			
	Full sample	High	Low	High	Low	High, low	Low, high	Low, low	High, high
RF	-0.013	-0.043	-0.009	-0.028	-0.012	-0.047	-0.028	-0.008	-0.034
	(0.003)	(0.013)	(0.003)	(0.010)	(0.003)	(0.014)	(0.010)	(0.003)	(0.029)
FS	-0.154	-0.150	-0.154	-0.116	-0.158	-0.163	-0.122	-0.157	-0.097
	(0.001)	(0.002)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)	(0.005)
2SLS (ETI)	0.083	0.285	0.061	0.240	0.074	0.286	0.229	0.052	0.352
	(0.018)	(0.084)	(0.017)	(0.089)	(0.019)	(0.086)	(0.082)	(0.017)	(0.300)
N	81,676	9,813	71,863	8,054	73,622	7,976	6,217	65,646	1,837

Notes: The table shows reduced form, first stage, and 2SLS regression results estimating the ETI for middle income families based on the first base year. Standard errors are clustered at the family level.

Figure 16: First Base Year Effect on MTR and Income
UC and CSU Enrollment Sample; Original Years



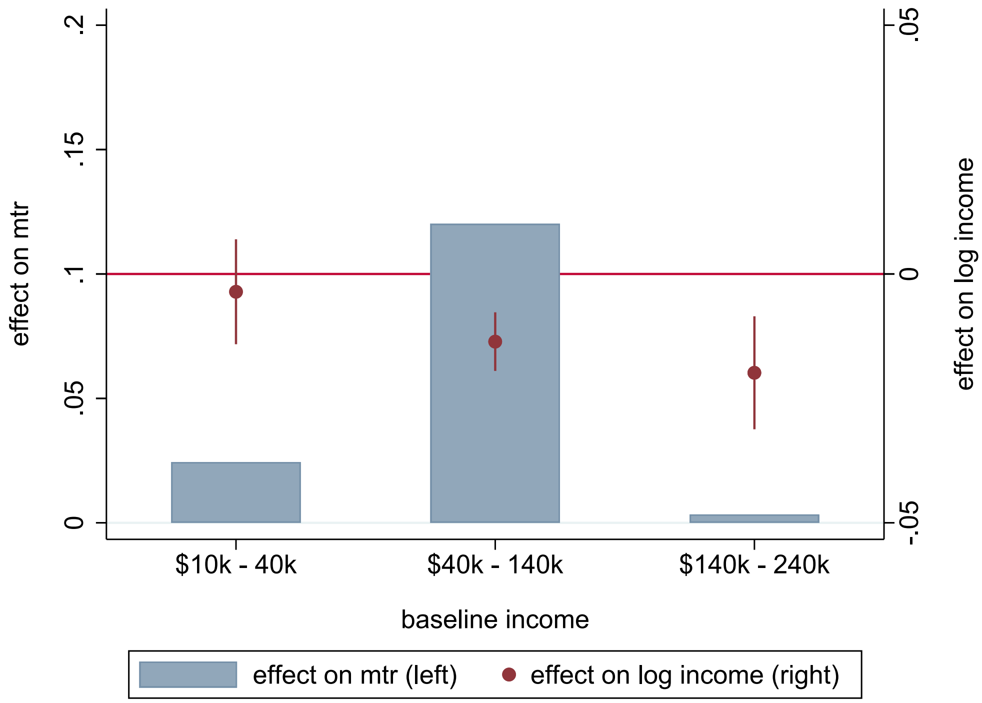
Notes: Separately by baseline income, the figure shows the first stage effect of the first base year on the simulated marginal tax rate from aid as bars (left axis) and the effect on log income in dots (right axis) with robust 95% confidence intervals.

Table 13: First Base Year Elasticity of Taxable Income – Middle Income Families
UC and CSU Enrollment Sample; Original Years

		By non-labor income share		By assets		By non-labor income share and assets			
	Full sample	High	Low	High	Low	High, low	Low, high	Low, low	High, high
RF	-0.015	-0.063	-0.010	-0.040	-0.013	-0.061	-0.032	-0.008	-0.083
	(0.005)	(0.024)	(0.005)	(0.017)	(0.005)	(0.027)	(0.017)	(0.005)	(0.052)
FS	-0.135	-0.129	-0.135	-0.086	-0.140	-0.144	-0.093	-0.140	-0.058
	(0.001)	(0.004)	(0.001)	(0.004)	(0.001)	(0.004)	(0.005)	(0.001)	(0.008)
2SLS (ETI)	0.113	0.491	0.071	0.463	0.095	0.424	0.344	0.060	1.424
	(0.037)	(0.186)	(0.035)	(0.204)	(0.038)	(0.185)	(0.187)	(0.036)	(0.926)
N	22,488	2,432	20,056	2,085	20,403	2,022	1,675	18,381	410

Notes: The table shows reduced form, first stage, and 2SLS regression results estimating the ETI for middle income families based on the first base year. Robust standard errors in parentheses.

Figure 17: First Base Year Effect on MTR and Income
UC and CSU Enrollment Sample; Expanded Years



Notes: Separately by baseline income, the figure shows the first stage effect of the first base year on the simulated marginal tax rate from aid as bars (left axis) and the effect on log income in dots (right axis) with 95% confidence intervals clustered at the family level.

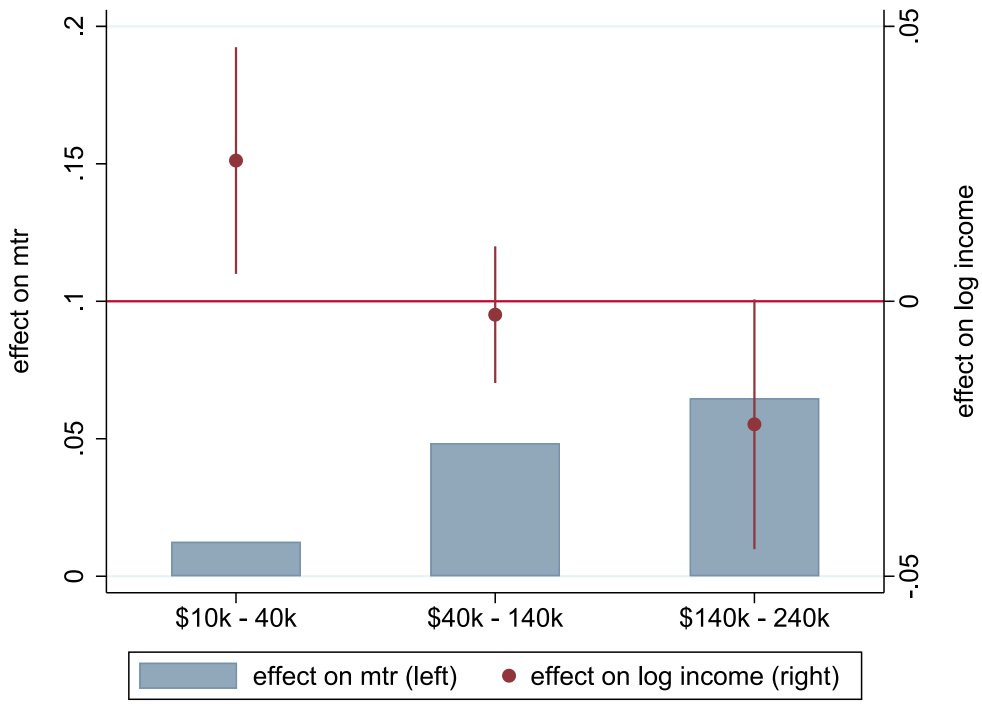
Table 14: First Base Year Elasticity of Taxable Income – Middle Income Families
UC and CSU Enrollment Sample; Expanded Years

		By non-labor income share		By assets		By non-labor income share and assets			
	Full sample	High	Low	High	Low	High, low	Low, high	Low, low	High, high
RF	-0.014	-0.048	-0.010	-0.028	-0.013	-0.047	-0.023	-0.009	-0.057
	(0.003)	(0.014)	(0.003)	(0.011)	(0.003)	(0.015)	(0.011)	(0.003)	(0.032)
FS	-0.141	-0.136	-0.141	-0.092	-0.146	-0.150	-0.098	-0.146	-0.069
	(0.001)	(0.002)	(0.001)	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)	(0.005)
2SLS (ETI)	0.097	0.352	0.070	0.306	0.086	0.311	0.235	0.064	0.829
	(0.021)	(0.102)	(0.020)	(0.120)	(0.021)	(0.101)	(0.110)	(0.020)	(0.467)
N	70,977	8,217	62,760	6,632	64,345	6,777	5,192	57,568	1,440

Notes: The table shows reduced form, first stage, and 2SLS regression results estimating the ETI for middle income families based on the first base year. Standard errors are clustered at the family level.

Appendix B: Estimates of the Reduced Form ETI in Response to a Second Child Enrolling for High Income Families, using UC & CSU Enrollment Sample

Figure 18: Effect on MTR and Income for 1 $\rightarrow$ 2 Enrolled
UC and CSU Enrollment Sample



Notes: Separately by baseline income, the figure shows the first stage effect of the two kids aid schedule on the simulated marginal tax rate from aid as bars (left axis) and the effect on log income in dots (right axis) with 95% confidence intervals clustered at the family level.

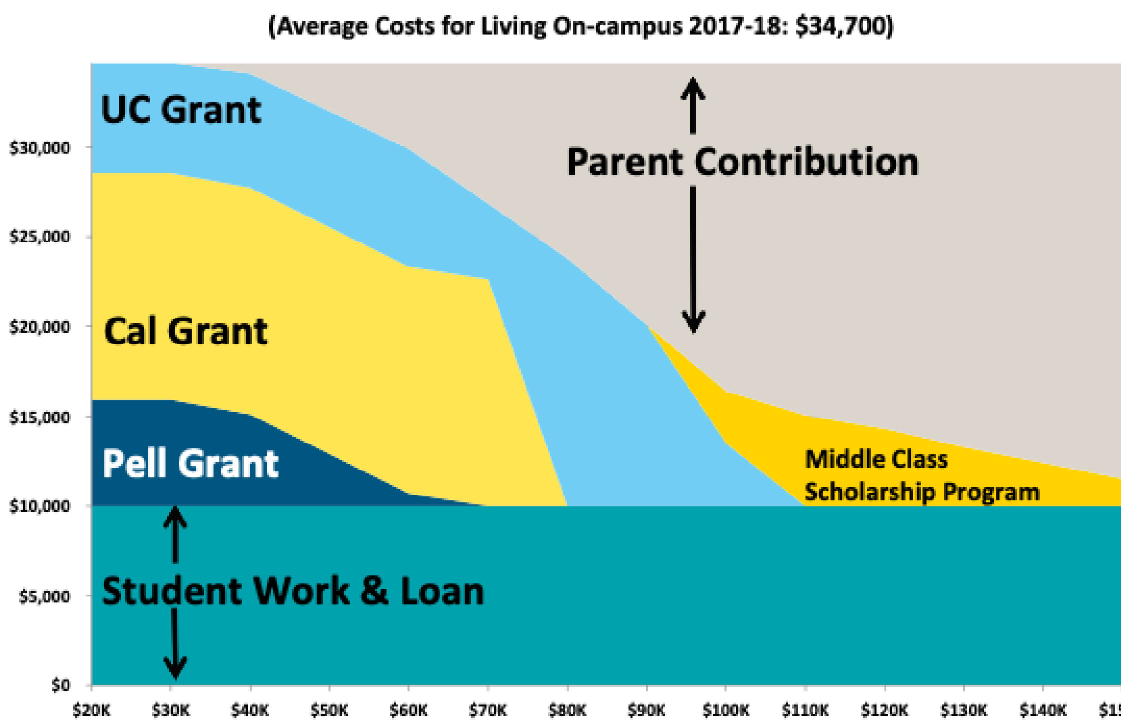
Table 15: Elasticity for 1 $\rightarrow$ 2 Enrolled
UC and CSU Enrollment Sample

	Full sample	By non-labor income share: High	By non-labor income share: Low	By assets: High	By assets: Low
RF	-0.022	-0.062	-0.017	-0.023	-0.024
	(0.012)	(0.043)	(0.012)	(0.022)	(0.014)
FS	-0.076	-0.071	-0.076	-0.043	-0.093
	(0.004)	(0.011)	(0.004)	(0.005)	(0.005)
2SLS (ETI)	0.296	0.868	0.224	0.535	0.255
	(0.153)	(0.639)	(0.158)	(0.550)	(0.148)
N: RF	4,211	481	3,730	1,375	2,836
N: FS	3,069	336	2,733	1,045	2,024

Notes: The table shows reduced form, first stage, and 2SLS regression results estimating the ETI for high income families based on changing from one to two kids enrolled. Standard errors are clustered at the family level.

Appendix C: Additional Figures and Tables

Figure 19: UC Education Financing Model (EFM)



Notes: This figure shows the University of California Education Financing Model (EFM), which details intended aid and net cost by parent income, along with aid sources.