Analysis Plan

Project Name: Examining the impacts of the COVID-era direct payments during the transition to adulthood - Child Tax Credit of 2021

Project Code: 2312

Date Finalized: 1/3/2025

The content of this document does not necessarily reflect the views or the official positions of the U.S. Department of the Treasury or the Internal Revenue Service and has been reviewed to ensure that no confidential information is disclosed.

Project description

In 2021, the American Rescue Plan (ARP) expanded the coverage of the Child Tax Credit to better assist families who care for children.[1] The ARP expansion was designed to reduce child poverty by supplementing the earnings of families receiving the tax credit, and making the credit available to a significant number of new families. The revisions increased the credit amount to $3,000 for older children (compared to $2,000), made the credit fully refundable (compared to partially refundable) and included advanced monthly payments in July - December (compared to a one-time tax refund).

Finally, critical to our evaluation, the Child Tax Credit of 2021 extended the age limit to being claimed as a dependent from 16 and under to 17 and under as of the end of the year (December 31, 2021). Due to this change, most of the families with the oldest children eligible would have received these direct payments during the fall and spring of the child's senior year of high school. That is, the timing of these payments coincides with the period in the college choice process when teenagers and their families make decisions about whether and where to enroll in college. In this evaluation, we measure the effects of eligibility for the Child Tax Credit during this critical point in the transition to adulthood on teenagers' decisions to enroll in college, among other outcomes.

Our evaluation design compares outcomes for slightly younger children whose families were eligible to claim them for the purposes of the Child Tax Credit of 2021 (and 2020) to the outcomes of slightly older children whose families were ineligible to claim them for these tax benefits. We estimate the combined effect of eligibility for the Child Tax Credits of 2020 and 2021, since the expansion in eligibility from 16 to 17 year olds between 2020 and 2021 makes the eligibility cut off for both credits dependent on whether children were born before or after January 1, 2004. The ability to use this regression discontinuity design to make causal claims about the effects of

[1] https://home.treasury.gov/policy-issues/coronavirus/assistance-for-american-families-and-workers/child-tax-credit.

eligibility for these tax benefits hinges on the assumption that families with slightly younger children only differ from families with slightly older children in their eligibility for the tax benefit.

Research Questions

We have one primary research question and two sets of secondary research questions. Both our primary and secondary research questions aim to measure the causal impacts of eligibility for the Child Tax Credit of 2020 and 2021. Before outlining our planned analysis of the causal effects of eligibility for these benefits, we describe two additional sets of analyses that we plan to conduct.

This preliminary analysis intends to provide evidence on the credibility of our identification strategy (evaluation design) and evidence of what the treatment that we evaluate is in practice.

These research questions are:

1. What is the relationship between eligibility for the Child Tax Credit of 2020 and 2021 and receipt of tax benefits (or after tax income)?

2. What evidence supports (or discredits) the idea that families with slightly younger or older children are similar to one another based on observable characteristics?

Next, we turn to our causal research questions. Our primary research question is:

3. What is the effect of eligibility for the Child Tax Credit of 2020 and 2021 on college enrollment and tax filing behaviors in 2022 among young adults from relatively low-, middle-, and high-income families?

Our secondary research questions seek to answer the questions:

4. How do the effects of eligibility for these credits vary by other subgroups (e.g., race, location)?

5. What are the effects of eligibility on other outcomes (e.g., college characteristics, tax filing behavior, connection to the labor market)?

Data sources

This analysis will use centrally housed and de-identified administrative data maintained by the U.S. Internal Revenue Service (IRS) to meet the needs of research analysts.[2] We describe the data sources in additional detail in Table 1.

Most of our analysis uses administrative data that are reported to the IRS on behalf of individuals. Regardless of whether an individual files their taxes, employers, colleges, government agencies, and other entities share data on the individual with the IRS for the purposes of tax administration. These data include forms such as the W-2 or 1099 (for wages and taxes withheld) and 1098-T (for

[2] The IRS provided data access to do this analysis and reporting on the findings as part of the 2023 Statistics of Income Joint Statistical Research Program (JSRP).

reporting higher education expenses), among others, that are known as "information returns." The Social Security Administration (SSA) also shares data on individuals' dates of birth with the IRS.

In addition, taxpayers share self-reported information with the IRS that often is not captured in other administrative data sources. Self-reported data are reported to the IRS only when individuals file their taxes and complete a specific form. The main reason we use self-reported data is to link children to tax units, which could be thought of as the child's family. Tax units include primary filers, secondary filers when a married couple files jointly, and children who are claimed as dependents. The self-reported information that we plan to use to define tax units is captured in the Form 1040.

For our heterogeneity analysis, we link the adolescent's location to data at the census-tract and zip-code levels that defines vulnerability to shocks or social disadvantage at the community level. These data come from the Centers for Disease Control Social Vulnerability Index (SVI) and from Opportunity Insights, and are described in more detail in the section on heterogeneous treatment effects, below.

In addition to heterogeneity in social disadvantage at the community level, we intend to look at heterogeneity by (predicted) race. We do not directly observe race or ethnicity for the children in our sample. Instead, we will make use of race and ethnicity imputations already generated by the IRS. Again, this is described in more detail in the section on heterogeneous treatment effects, below.

Finally, we use publicly available data from the Integrated Postsecondary Education Data System (IPEDS), which includes information on colleges, including college type (i.e., 4-year or 2-year), graduation rates, acceptance rates, tuition and fees, among many other measures. For children who enroll in college, we link this information to the child using the Employer Identification Number (EIN) for the school listed on the Form 1098-T that the college issues to the child.

Table 1. Data sources for examining the effects of eligibility for the Child Tax Credit of 2020 and 2021

Data Source	Description	Primary Use
Social Security Administration Birth Records, shared with IRS for purposes of tax administration	All births and people issued Social Security Numbers that are shared with the IRS for purposes of tax administration.	Define sample
Form 1098-T: Tuition Statement	An information return that a college or university sends to the IRS for enrolled students.	Measure college enrollment outcomes.
IPEDS: Integrated Postsecondary Education Data System	Publicly available data on college characteristics maintained by the U.S. Department of Education	Measure characteristics of colleges where students enrolled.

Form 1040: U.S. Individual Income Tax Return	A form that a taxpayer provides when filing their taxes. Used to claim children as dependents, claim tax benefits, list amounts of income from different sources, and, ultimately, used to determine the amount of tax due/refund owed.	Used to link children to tax units, refine the analytic sample, to include measures of family characteristics as covariates, and use these measures to assess the validity of the quasi-experimental evaluation design.
Form W-2: Wage and Tax Statement	An information return on wages that an employer sends to the IRS for their employees.	Used to measure income and predict eligible for the tax benefit. Used to measure work force participation as a covariate and outcome of interest for the target children.
Form 1099-NEC: Non-Employee Compensation	An information return on compensation that an employer sends to the IRS for their contractors.	
CDC/ATSDR Social Vulnerability Index (CDC/ATSDR SVI)	Census tract-level indicators of social vulnerability/disadvantage.	Define subgroups for heterogeneity analysis.se
Opportunity Insights	Census-tract- and zip-code-level indicators of social mobility.	Define subgroups for heterogeneity analysis.
IRS imputations of individual race and ethnicity	Probability score of race and ethnicity based on name and location.	Define subgroups for heterogeneity analysis.

Sample identification

Units of analysis

It is helpful to consider two relevant units of data in our analysis. The first is the children born around January 1, 2004. The second is the families, or tax units, who claim these children as dependents.

Analysis for target children

Our starting point for identifying our sample uses information for the children - namely their birthday. Our primary outcomes of interest also are measured for these children. For example, we can measure whether the IRS receives a Form 1098-T from a college or university that is linked to the child as a way to measure whether the child enrolled in college in a given year.

Analysis for tax units linked to target children

Our analysis also relies on tax unit information. This is because many tax records are at the return level and capture information for a tax unit. Tax benefits also are paid to families who claim eligible dependents, making the tax unit the relevant unit who receives the benefit. Tax units include primary filers and others associated with their return. Others in the tax unit could include children who are claimed as dependents and secondary filers, who appear when a married couple chooses to file jointly.

While our analysis relies on data from 2003 through 2022, corresponding to when the children were born to when they reached college-going age, most of the children in our sample will not file their taxes as independent tax filers or have information returns associated with them until they reach young adulthood and begin working or enroll in college.[3] Instead, they typically appear in the tax return data when a primary tax filer—usually a parent—claims them as a dependent. Thus, a main reason we use tax unit information is that it allows us to follow the same family unit for the target child born around January 1, 2004 over time (i.e., creating a panel of data for a tax unit for TY 2019 - 2021).

By generating a panel of data for a specific tax unit, we are able to measure characteristics of the families during a baseline period, before the implementation of the Child Tax Credit of 2021 and 2020. Baseline characteristics are useful for assessing whether families with slightly younger children are similar to those with slightly older children. These baseline measures also are used as covariates in our regression models to improve precision. Finally, we use baseline characteristics to define our overall sample of interest and to create subgroups. For example, we use baseline characteristics to better predict eligibility for tax credits, which is partially determined by the family structure of the tax unit (e.g., the number of children in the house, whether the return is for a single taxpayer or married taxpayers who file jointly) and family income.

Another way we use tax unit information is to describe the amount of tax benefits that the target child's family is predicted to receive and receives in practice. We focus on the tax unit for this analysis, since tax benefits are paid to the families who claim eligible dependents, rather than the child themselves. Using the tax unit also makes sense conceptually, since families' finances arguably are more relevant than those of the teenager for understanding what college choices are financial options for them when considering whether and where to apply and attend college.

Sample inclusion

As stated above, our starting point for identifying our sample is children born around January 1, 2004. We identify these children using Social Security Administration birth records and include only children who have valid Social Security Numbers (SSNs) that make them eligible to work (an eligibility requirement to be claimed as a dependent for the purposes of the Child Tax Credit).[4]

Our evaluation design builds off earlier work that uses age eligibility rules for dependents to identify the causal effect of eligibility for these benefits on children's long run educational and

[3] A child might also have an information return for their health insurance coverage associated with them; however, we do not currently plan to use these data as part of our analysis (for example, as an additional way to link children to primary filers).

[4] https://www.irs.gov/credits-deductions/tax-year-2021-filing-season-2022-child-tax-credit-frequently-asked-questions-topic-e-commonly-asked-immigration-related-questions#:~:text=A2.-,Yes.,Tax%20Credit%20for%20that%20child.

labor market outcomes (Barr et al., 2022)[5] and parent's labor market participation (Lippold & Luczywek, 2023).[6] In our case, we compare outcomes for children born around January 1, 2004, the cut off to be age eligible for the Child Tax Credit of 2020 and 2021. Children born at the end of 2003 are slightly older and do not meet the age eligibility requirements to be claimed as a dependent for the Child Tax Credit of 2020 and 2021. Children born in early 2004 are slightly younger and meet the age eligibility requirements to be claimed as a dependent for the Child Tax Credit of 2021 and 2020.

Consistent with the sample used in the prior work described above, we anticipate that our primary sample will include children born December 1, 2003 - December 23, 2003 and children born January 9, 2004 - January 31, 2004. We exclude children born in the 16 day period from December 24, 2003 - January 8, 2004 (8 days on either side of the cut off) to limit the potential that our sample includes families who manipulated their child's birthday around the holidays and cut off for eligibility.

The earlier work focuses on payments made during infancy and early childhood, whereas in our setting we focus on payments made during late adolescence. In our setting, we may be more comfortable considering a wider bandwidth of births, since the developmental differences of being a few months older diminish over time. Thus, while we anticipate that our primary sample will include children born in the 31 day band around the end of the year (December 1, 2003 - January 31, 2004), we also plan to run robustness checks for wider birthday bands.

Recall, our primary analysis examines how being eligible for additional tax benefits, and the financial liquidity these benefits provide, when teenagers are making college choice decisions shape whether and where they enroll in college. Thus, more relevant in our setting than developmental differences related to relatively small changes in age is the timing of when students graduate high school, i.e., their high school cohort. While we do not observe high school graduation year directly, we can predict when most of the target children in our sample would graduate based on their age and when they entered kindergarten, which varies at the state and local levels. We may be concerned about including children in our sample who are not seniors in high school when payments are made, because these children would not have the opportunity to use the funds to influence their college choice decision. This measurement error could introduce attenuation bias. Thus, we plan to account for this potential concern as outlined below.

Since our analysis focuses on college choice decisions, we must balance the benefits of widening our inclusion criteria to increase sample size with the risk of introducing unwanted variation in high school graduation year among children in our sample. Widening the birth range for inclusion could introduce variation in high school graduation year through two key pathways. First, a wider inclusion range is more likely to have overlap with birthdate cut offs for school entry. We can partially account for school entry policies that would make it more likely for the slightly older

[5] Barr, Andrew, Jonathan Eggleston, and Alexander A. Smith. "Investing in infants: The lasting effects of cash transfers to new families." *The Quarterly Journal of Economics* 137, no. 4 (2022): 2539-2583.
[6] Lippold, Kye, and Beata Luczywek. "Estimating Income Effects on Earnings Using the 2021 Child Tax Credit Expansion," September 29, 2023. https://beata-luczywek.com/files/Luczywek_JMP.pdf.

children to graduate high school before ACTC payments were made, by excluding children living in states with overlapping school entry policies from our analysis (see exclusion criteria below). Second, children near official age cutoffs for school entry could be more likely to be held back, since they are the youngest in their grade, or more likely to start school early, by skirting school entry rules. Since we are unable to observe this second pathway in our data a more conservative criteria for birthdate inclusion may be warranted.

Given these tradeoffs and precedent for using a December - January birthdate range for sample inclusion, we plan to use this 31-day window to define our primary sample. However, we will use our data to assess the credibility of this evaluation design choice. If we discover differences in observable characteristics, then we will use a data driven approach to identify a sample where children born before and after January 1, 2004 appear more comparable on observable characteristics. We anticipate using data-driven approaches to define these bands among children born in the 90 day window around the end of the year (November 15, 2003 - February 15, 2004).

Sample exclusion

While our primary criteria for sample inclusion depend on information for the child, sample exclusions criteria depend primarily on data for the tax unit. (We describe the process of linking children to tax units in more detail below.)

Starting with the inclusion sample described above, we further refine our sample to try to account for other programs that use similar age-based eligibility cutoffs (that could determine high school cohort or eligibility for unobservable benefits), their likely eligibility for the benefits examined, and other data quality considerations. We plan to account for these issues by making the following sample exclusions:

Relevant policies and programs using birthdays near January 1, 2004 for eligibility

1. We plan to exclude children who are living in states known to have birthdate cutoffs for school entry that coincide with cutoffs for eligibility for the Child Tax Credit of 2020 and 2021. As a result, students living in these states would be in different high school cohorts and go through the college choice process in different years.

   These states are California (December 2, 2003), Connecticut (January 1, 2004), Hawaii (January 1, 2004), Michigan (December 1, 2003), Vermont (January 1, 2004), and Washington, DC (December 31, 2003).[7]

   We also plan to exclude children for whom we cannot determine with any certainty where they lived by the time they turn five. This means we exclude children who were never claimed as dependents between TY 2008 and TY 2004.

[7] Data for school entry cutoffs by state were compiled and generously shared by Dr. Elizabeth Bedard (see for example, Bedard & Dhuey 2012) and Joel Moore, Assistant Director of State Relations at the Education Commissions of the States (see for example, Kindergarten Entrance Ages: A 35 Year Trend Analysis).

2. We plan to exclude children living in the U.S. territories during the school entry period, due to potential other policy and schooling differences during this period.

Likely eligibility for the Child Tax Credit of 2021

3. We plan to exclude children in tax units that we predict are not income eligible to receive tax benefits from the Child Tax Credit of 2021.

   To determine income eligibility, we impute the age for the target child to be age-eligible for the Child Tax Credit of 2021 and plan to use the following additional information to predict expected benefit amount:

   - 2019 AGI (or its proxy); and
   - family structure and filing status in the year the target child is linked to a tax unit during the baseline period.

   Using this information, if the expected benefit amount for the Child Tax Credit in 2021 is $0, then we exclude the target child from the analysis.

   We discuss this approach in greater detail in the linking target children to baseline tax units (TY 2019) and planned analysis for research question one sections.

4. We plan to exclude children who died prior to January 1, 2020, the end of our baseline year data.

5. We plan to exclude target children who file as independent tax filers and are not claimed as dependents during any of the baseline years (TY 2019, TY 2018, or TY 2017).

6. We plan to exclude children living in the U.S. territories during the baseline period, since eligibility rules and distribution of advanced payments differed in these locations.[8]

Data quality considerations

7. We plan to exclude children who we cannot link to a tax unit either during early childhood or during our baseline period. This means that our primary sample includes children who are claimed as a dependent at least once during early childhood (TY 2004 - 2008) and at least once as a teenager (TY 2017 - 2019).

8. We plan to exclude target children who we associated during the early childhood period or during the baseline period with multiple returns (e.g., claimed as a dependent more than once in a given year).

9. We plan to exclude children that have multiple birth dates reported.

[8] https://www.irs.gov/credits-deductions/2021-child-tax-credit-and-advance-child-tax-credit-payments-topic-i-us-territory-residents-and-advance-child-tax-credit-payments#:~:text=A2.,pay%20U.S.%20social%20security%20taxes.

While our primary analysis includes these sample exclusions, we plan to implement robustness checks to better understand the sensitivity of our results to these decisions. These robustness checks are described in more detail in the "Robustness checks for sample selection" section.

Linking children to tax units

As described in the unit of analysis section, our analysis requires that we link children to tax units at different points in time and for different purposes. Table 2 describes these instances and the relevant tax years.

Table 2. Linking children to tax units for our primary analysis

<table>
<tr><th>Tax Year</th><th>Purpose</th></tr>
<tr><td>2008</td><td>Identify where the child lived when school entry could have differed based on their location and date of birth.</td></tr>
<tr><td>2019</td><td>Establish a tax unit during the last year in which all children in the sample were eligible for tax benefits.

Use data from this year to:
define covariates;
define measures used to assess validity of evaluation design;
define subgroups;
predict eligibility for the Child Tax Credit of 2020;
predict eligibility for the Child Tax Credit of 2021;
predict overall tax benefit receipt in TY 2020 and 2021;
observe receipt of tax benefits for the tax unit in tax year 2020 (including overall refund amount, Child Tax Credit amount); and
observe receipt of tax benefits for the tax unit in tax year 2021 (including overall return amount, total Child Tax Credit amount, advance portion amount of Child Tax Credit, regular portion amount of Child Tax Credit).</td></tr>
</table>

We plan to link children to tax units through a two step process:

1. First, we will search for the target child among children claimed as dependents. We start in the relevant year of interest. If necessary, we will go back tax years until the child is found. We will search in TY 2008 - TY 2004 during the early childhood period (primarily to find the location of the child at school entry). We will search in TY 2019 - TY 2017 to establish a baseline tax unit for the child.

   Note that we do not look in TY 2003, since we want the process of matching to be the same for the older and younger children. Only the older children could have been claimed in TY 2003, since the younger children had not yet been born.

2. Second, we will search for information returns and Form 1040 information for the primary and secondary filers linked to the child in step one in some cases. For example, we use information returns from TY 2019 as a measure of tax unit income to predict eligibility,

benefit amount, and after tax income in 2020 and 2021. This process allows us to find more up to date information for people who did not file (or claim the child as a dependent).

As noted in the exclusions section, in cases where we cannot link a child to a tax unit during either period, we exclude them from our primary sample. An implication of this decision is that our primary sample is among children claimed as a dependent at least once during early childhood and at least once during adolescence.

Linking target child to tax units at school entry (TY 2008)

We use the following procedure to identify target children living in states with school entry dates between December 1, 2003 and January 1, 2004:

1. Link target child to tax units for primary and secondary filers by searching for the target child to be claimed in TY 2008 - 2004.
    a. Use the most recent information available to link the child to a primary and (if applicable) secondary filer.
    b. If the child is never found, exclude them from the primary sample.
2. Identify the location for the child in the year the target child was linked to the tax unit using the 1040 form.

Linking target child to tax units at the baseline year (TY 2019)

We use the following procedure to link target children to tax units in the baseline year (TY 2019).

1. **Linking stage:** Search among 1040 information on children claimed as dependent for the target child between TY 2019 -2017. Link the child to the primary and secondary filers in the most recent tax year in which the child is claimed. (Recall, if the child is never found, exclude them from the primary sample.)
2. **Information stage:**
    a. If the child was claimed in TY 2019, then use their 1040 information to predict eligibility for the Child Tax Credit of 2020 and 2021, among other measures.
    b. If the child was not claimed in TY 2019, then:
        i. Impute their family structure based on the most recent year they were claimed (TY 2018 or TY 2017)
        ii. Use information returns for the primary and secondary filer in TY 2019 as proxies for expected income (to predict eligibility, among other measures).

Transformations of data structure

Our planned analysis will include one record per target child. In some cases, as described above, the record will represent information about the target child themselves and in other cases will represent information about the tax unit linked to the target child.

Treatment of missing data

For our sample inclusion, our primary model uses a complete case approach where we only include target children if they have been claimed as a dependent during early childhood and adolescence. Thus, we know at least one tax return can be linked to the target child during either period.

For outcomes, we describe our treatment of missing data in the outcomes table below. Namely values will be imputed to 0, if a target child is not linked to a Form 1098-T. See discussion of limitations to using Form 1098-T data in the limitation sections focused on Form 1098-T Coverage.

Planned analysis

Research question 1: Relevance of age-based eligibility for Child Tax Credit of 2020 and 2021

Our first research question documents the relevance of eligibility for the Child Tax Credit of 2020 and 2021 to family's after-tax incomes during the period when the target child is making decisions about whether and where to attend college. To answer this question, we plan to define tax benefit receipt and benefit eligibility as outlined in Table 3. We describe our preferred approach for this analysis in the planned analysis section below.

Table 3. Measures of receipt and eligibility for tax benefits and income

Measure	Definition
After-tax income	Predicted and actual income after accounting for taxes and transfers for the tax unit
Child Tax Credit of 2020 amount	Predicted and actual total benefit amount for the tax unit and target child
Child Tax Credit of 2021 amount	Predicted and actual total benefit amount for the tax unit and target child (sum of advanced and regular portion)
Advanced proportion of Child Tax Credit of 2021 amount	(If feasible) Predicted and actual total advanced portion of the benefit amount for the tax unit and target child
Regular portion of Child Tax Credit of 2021 amount	Predicted and actual portion of the regular portion of the benefit amount for the tax unit and target child
Credit for Other Dependents of 2021 amount	Predicted and actual total benefit amount for the tax unit and target child

To calculate these different measures described in Table 3, we plan to use several alternative approaches that capture both predicted eligibility for these benefits and actual receipt of benefits:

1. Input baseline tax information as inputs into Taxsim to create predicted measures of benefit receipt in tax year 2020 and 2021.

2. Search for the baseline tax unit in tax year 2020 and 2021 in order to report actual benefit receipt for the baseline tax unit in these years. For this analysis, we will search for returns for the primary and (if applicable) secondary filer linked to the target child during the baseline period. We plan to sum benefit amounts across both returns when two returns are present, since the financial situation of the target child may be linked to either filer.

3. (if feasible) Search for the tax unit linked to the target child in tax year 2020 and 2021 to report actual tax credit benefit receipt in these years for the target child.

Approach one is our preferred approach, since it most closely aligns with describing the difference in tax benefits from being eligible for the Child Tax Credit of 2020 and 2021. Approaches two and three are informative for understanding actual benefit receipt.

These approaches also vary in whether they are determined using the baseline tax unit or target child information. Approaches one and two report benefit receipt for the tax unit identified at baseline, whereas approach three uses information on the target child, allowing the tax unit to change over time. That is the second approach characterizes the payments made to a tax unit, whereas the third approach characterizes the payments made to the target child.

A complication with our strategy in the second approach is that the adult who claimed the child during the baseline years may not be the same as the filer who would have received the the Child Tax Credit benefits in 2020 and 2021 (e.g., if divorced parents switch off claiming the child for the purposes of tax benefits). This could introduce measurement error in benefit receipt, but avoids endogeneity concerns from strategic filing since the tax unit is identified during the baseline year and fixed over time.

An additional complication could occur if the child was claimed on a return filed jointly by two parents at baseline, but the parents have divorced in the intervening year(s), and each files their own return in TY 2020 and 2021. To account for this, we will look for both the primary and secondary filer TINs in the tax return data in TY 2020 and 2021, and will total the benefit amounts sent to both adults and assign that total to the target child.

If the data allows, we will use a third approach for characterizing the benefit linked to the target child (rather than their baseline tax unit). This strategy focuses on finding the target child first among children claimed as dependents, and then linking that child back to a tax unit to determine the amount of benefits associated with that child (and their after tax income). Since some children may file their own tax returns (and not be claimed as a dependent), we will also look for their after-tax income. A benefit of this approach is that we can be more certain of the benefit receipt associated with the target child. A complication of this approach is that some target children may choose not to file or not be claimed as dependents, but still be part of the family structure identified during the baseline year. If in these cases, the family's financial situation is most relevant to the child's financial liquidity and college choice decision, we would not be fully capturing their actual financial situation. Further, we may expect families with slightly older children to be less likely to claim the child for benefits, since they have fewer benefits for which they are eligible.

Research questions 2-5: Primary specification model

Our empirical model is a regression discontinuity design that leverages the birthdate cutoff prior to January 1, 2004 to determine the causal impact of eligibility for the Child Tax Credit of 2020 and 2021 on our outcomes of interest. We adopt the local randomization justification for our regression discontinuity, and assume that, within a given window of birthdays around January 1, (in)eligibility for the Child Tax Credit is as good as random.[9] Our regression specification is as follows:

$$Y_i = \beta_0 + \beta_1 1[z_i > 0] + \beta_2 z_i + \beta_3 1[z_i > 0] \times z_i + X_i'\gamma + \varepsilon_i$$

(Equation 1)

Where Y_i is an outcome of interest, z_i is the number of days between the child's birthdate and January 1 (centered at zero), and $1[z_i > 0]$ is a binary indicator equal to one if child *i* is born on or after January 1. X_i is a vector of individual and tax unit covariates, defined above; in some models we may exclude these. The primary coefficient of interest is β_1, which identifies the impact of eligibility for the Child Tax Credit (the intent-to-treat estimate). We implement this model using ordinary least squares regression limited to the relevant window (described above).[10]

Research question 2: Investigating the credibility of the evaluation design

We plan to run statistical tests to provide evidence that there is not systematic sorting into treatment and control:

1. We plan to provide graphical evidence by plotting the density of the birthdates around January 1.
2. We plan to formally test if this density is the same on both sides of the cutoff by running a binomial test.[11] [12]

[9] Cattaneo, Matias D., Nicolas Idrobo, and Rocío Titiunik. "A Practical Introduction to Regression Discontinuity Designs: Extensions." *Elements in Quantitative and Computational Methods for the Social Sciences*, March 2024. https://doi.org/10.1017/9781009441896.
[10] Cattaneo et al. (2024) provide packages in R and Stata that implement local randomization regression discontinuity analyses. However, their packages rely on Fisherian inference, in order to be robust to small sample sizes. Given that our sample includes several hundred thousand children, we plan to rely instead on standard inference procedures that are valid in large samples, but will run robustness checks using their package.
[11] The test is discussed here: Cattaneo, Matias D., Nicolas Idrobo, and Rocío Titiunik. "A Practical Introduction to Regression Discontinuity Designs: Extensions." *Elements in Quantitative and Computational Methods for the Social Sciences*, March 2024. https://doi.org/10.1017/9781009441896.
[12] This density test is compatible with our plan to exclude a "donut hole" of children whose birth dates fall proximate to the January 1st threshold (December 24, 2003 - January 8, 2004, where we expect to see manipulation). Instead of testing for manipulation of the running variable at the threshold, we will use a binomial test to evaluate whether there is manipulation of the running variable outside the donut hole window.

3. We plan to check for systematic differences in our control and treatment groups by running our main specification (Equation 1, excluding the covariate vector) on predetermined covariates (listed in Table 4 below and marked with validity as a use). Running our specification on predetermined covariates and showing evidence of no treatment effect provides evidence of balance on those covariates.

Our regression discontinuity model relies on the assumption that, within a window around the cutoff in the running variable (in this case, the number of days between the child's birth date and January 1), assignment to "treatment" (in this case, eligibility for the Child Tax Credit of 2020 and 2021) is as good as random. This requires selection of an appropriate window. For our main specification, as described above, we propose to follow Barr et al. (2022) and exclude children from the sample whose birthdays fall more than 31 days from January 1. However, as a robustness check, we will also implement the data-driven window selection approach presented in Cattaneo et al. (2024), and implemented using the rdwinselect package available in both R and Stata.[13]

We plan to investigate the credibility of the design for the overall sample and within each subgroup of interest (low-income tax units, middle-income tax units, high-income tax units).

We describe additional planned analysis to investigate the validity of our design and sensitivity of our analysis to these analytic choices in the planned robustness check section.

Note that we plan to rely on local randomization for the validity of our regression discontinuity design; that is, conditional on falling in the window around the discontinuity, assignment to treatment is as good as random. However, if our tests of balance on covariates show evidence of correlation between covariates and our running variable, then we may fall back on the slightly less strict assumptions required for implementing a continuity-based RD.

Research question 3: Causal impacts of eligibility on college enrollment and tax filing behaviors

We plan to measure the causal impacts of eligibility for the Child Tax Credit of 2020 and 2021 for target children living in low-income, middle-income, and high-income households separately. That is, we plan to run three sets of analysis using equation 1 where we subset our sample to each of the income groups of interest.

In addition to reporting the average effects of eligibility on college enrollment and tax filing behaviors (see definition of outcomes in the outcomes section below), we plan to show the impacts visually by plotting mean outcomes binned by birthdate.

Inference criteria, including any adjustments for multiple comparisons:

We will use a cutoff of p = 0.05 to determine statistical significance (with stars according to + p = 0.10, * p = 0.05, ** p = 0.01). All tests will be two-tailed.

[13] We are aware of a potential bug in the rdwinselect package for Stata and if not resolved by time of implementation, we will use the package in R.

Since we have one primary outcome in a given domain (college enrollment or tax filing) and are interested in drawing separate conclusions within different income groups (low-, middle-, and high-income), we do not plan to adjust for multiple comparisons when reporting findings for the OES abstract.[14]

Standard errors and inference criteria

We plan to use robust standard errors that cluster on the tax unit. Clustering will occur when more than one target child (for example, twins) are claimed in the baseline year by the same tax unit.

We intend to use large sample methods for inference. That is, we run OLS regressions in the relevant window, using robust standard errors clustered by tax unit. However, we will also run our regressions using the rdlocrand package provided by Cattaneo et al. (2024), which employs Fisherian inference, to determine if our conclusions hold using this alternate inference procedure.

Research question 4: Additional subgroup analysis

For our analysis on other priority subgroups, we plan to continue to use our primary specification model (equation 1); however, in this case we plan to subset the analysis to include only target children who are part of the relevant subgroup of interest (see subgroups section).

For our subgroup analysis, we plan to further subset our analysis to include only baseline tax units who we define as low- and middle-income households.

Research question 5: Secondary outcomes

Finally, we plan to use our primary specification model (equation 1) to look at the effects of eligibility for the Child Tax Credit of 2020 and 2021 on additional outcomes. We plan to conduct analysis for the primary, secondary, and other outcomes for each of the three income groups. For other subgroup analysis, we plan to measure the effects only for the primary and secondary outcomes.

Administrative data measures and outcomes

Baseline measures

We use tax unit information during the baseline year to generate covariates, (in most cases) to generate subgroups of interest, and create exogenous measures of predicted benefit amount and after-tax income for tax years 2020 and 2021. These measures capture information for the tax unit, rather than for the target child.

[14] Rubin, Mark. "Inconsistent multiple testing corrections: the fallacy of using family-based error rates to make inferences about individual hypotheses." *Methods in Psychology* (2024): 100140.

Covariates

We plan to use covariates in our regression models to improve precision and to better understand the credibility of our evaluation design in making causal claims (Research Question 2). We define the baseline measures and their use in our analysis in Table 4.

Table 4. Baseline measures and covariates

Measure	Definition	Use
Location		
State in TY 2019	Indicator for each of the 50 states and the District of Columbia and a missing indicator (in cases where no location available on Form 1040).	Fixed effects
Target child linked to tax unit		
in TY 2019	1 if child linked to tax unit using TY 2019 data 0 otherwise	Covariate Validity
in TY 2018	1 if child linked to tax unit using TY 2018 data 0 otherwise	Covariate Validity
in TY 2017	1 if child linked to tax unit using TY 2017 data 0 otherwise	Validity[15]
Years claimed as a dependent	Number of years claimed as a dependent in TY 2019, TY 2018, and TY 2017	Covariate Validity
Consistently claimed	1 if child linked to same tax unit who filed in TY 2019 - 2017[16] 0 otherwise, including if child not claimed in one or more years	Covariate Validity
Family composition in baseline year child linked to tax unit		
Married filing jointly	1 if primary and secondary filer are married and filing jointly 0 otherwise	Covariate Validity

[15] Not included as a covariate, since this measure would be collinear with the linking indicators for TY 2019 and TY 2018.
[16] The same tax unit means the child was claimed by the same person or the same two people each of the three years.

Single filer	1 if primary filer files as head of household, single filer, or married filing separately 0 otherwise	Validity
Number of dependents	Number of dependents claimed the year the target child is linked to a tax unit during the baseline period	Covariate Validity
Tax unit Child Tax Credit Benefit amount in baseline year child linked to tax unit		
Refundable child tax credit amount claimed by tax unit in baseline year	Amount of refundable child tax credit benefit for the tax unit; $0 if Child Tax Credit is not claimed.	Covariate Validity
Non-Refundable child tax credit amount claimed by tax unit in baseline year	Amount of refundable child tax credit benefit for the tax unit; $0 if Child Tax Credit is not claimed.	Covariate Validity
Information returns for primary or secondary filer in TY 2019		
Tax unit has two adult earners	1 if any positive income reported on W-2 or 1099-NEC linked to primary and secondary filer in TY 2019 0 otherwise (including for single filers)	Covariate Validity
Tax unit has one adult earner	1 if any positive income reported on W-2 or 1099-NEC linked to only one of the primary and secondary filers in TY 2019, including single filers with positive income 0 otherwise	Covariate Validity
Income measure	Adjusted gross income for TY 2019 filers. Total earnings reported on W-2 and 1099-NEC for non-filers in TY 2019 (based on primary and secondary filers linked to target child during baseline period); 0 if no W-2 or 1099-NEC	Sample selection Covariate Validity
Has mortgage	1 if Form 1098 Mortgage Interest Statement linked to primary filer in TY 2019 0 otherwise	Covariate Validity
Social Security retirement or disability	1 if SSA-1099 linked to primary filer in TY 2019	Covariate Validity

(SSDI) income for primary filer	0 otherwise	
Has interest income	1 if 1099-INT (interest) linked to primary filer in TY 2019 0 otherwise	Covariate Validity
Has dividend income	1 if 1099-DIV linked to primary filer in TY 2019 0 otherwise	Covariate Validity
Has Unemployment Compensation income	1 if 1099-G with a positive value in Box 1 is linked to the primary or secondary filer in TY 2018 0 otherwise	Covariate Validity
Information returns for target child		
Employment	1 if any positive income reported on W-2 or 1099-NEC linked to target child in TY 2019 0 otherwise	Covariate Validity
Enrolled in college	1 if Form 1098-T linked to child 0 otherwise	Covariate Validity
Female	1 if female on birth certificate 0 otherwise[17]	Covariate Validity

Subgroups

Our primary analysis examines the causal effect of eligibility for the Child Tax Credit of 2021 (and 2020) among relatively low-income, middle-income, and high-income families, as measured by the baseline tax unit linked to the target child. We plan to define inclusion into one of these groups using a continuous measure for adjusted gross income (AGI) in 2019. We also plan to interact eligibility for the tax benefits (i.e., the treatment) with the continuous measure of tax unit income as a robustness check. In reference to Equation 1, this robustness check will entail interacting the binary indicator for the treatment ($1[z_i > 0]$) with the continuous measure of tax unit income.

Additionally, we are interested in learning about the heterogeneity in treatment effects for different sub-populations, specifically among members of socially disadvantaged communities or

[17] We will include an indicator for missing, if no data are available.

groups that have experienced systemic discrimination. We outline how we define these subgroups in Table 5 and in greater detail below.

Our subgroups are defined in two ways: individual-level characteristics, and location-based measures. Our first individual-level measure is based on AGI or its proxy as noted above. We use this measure for our primary analysis and examine impacts on all outcomes. Other subgroup measures are used for our secondary analysis on subgroups that measure the effects on primary outcomes only.

Our second individual-level measure is race and ethnicity. We do not observe race or ethnicity in our data; however, the IRS has developed race imputations using Bayesian Improved First Name and Surname Geocoding (BIFSG). This generates a probability that an individual belongs to a certain racial/ethnic group. We will assign an individual to a given group if their probability of belonging to that group is greater than 0.75.[18] Race imputations are available for the primary filer on a tax return only, so we do not know the imputed race of the target child. We use the imputed race of the primary filer associated with the target child in our link year to proxy for the race of the target child. The race/ethnicity combinations we are able to identify are non-Hispanic white, non-Hispanic Black, non-Hispanic Asian, and Hispanic.

To construct our location-based measures, we will rely on the address information for the target child in the link year (the most recent year, of 2017-2019, in which the child is claimed as a dependent and thus can be linked to a tax unit).

Our first location-based measure is the Social Vulnerability Index from the CDC. The SVI uses American Community Survey five-year estimates to generate 15 measures of vulnerability (based on poverty status, race, and disability, among others).[19] It ranks Census Tracts on the proportion of people in the tract who are vulnerable according to these measures, creating a final percentile ranking of all Census Tracts in the US compared to one another. We will use their rankings as of 2020 to identify individuals who live in high vulnerability, medium vulnerability, and low vulnerability Census Tracts, as defined by the tract scoring in the top, middle, and lowest third, out of all tracts in the country. Since our data on target children gives us the ZIP code and not the Census Tract, and Census Tracts and ZIP codes do not have a 1:1 correspondence, we will assign the child to a census tract using the Census 2020 ZIP code tabulation area (ZCTA) to Census Tract relationship file.[20]

---

[18] Elzayn et al. (2023) estimate the rates of false positives and negatives, looking only at estimated probabilities of Black and non-Black. A 0.75 threshold produces a false positive rate of 3.4% and a false negative rate of 53%. In the robustness check section, we discuss how we will examine additional thresholds. . Elzayn, Hadi, Evelyn Smith, Thomas Hertz, Arun Ramesh, Robin Fisher, Daniel E. Ho, and Jacob Goldin. "Measuring and Mitigating Racial Disparities in Tax Audits," January 30, 2023.
https://github.com/jacobgoldin/jg_website/blob/35c7e44419b0c3473041229c1f82b5a96e66b04d/audit%20disparities%201-30-23.pdf.

[19] https://www.atsdr.cdc.gov/placeandhealth/svi/index.html.

[20] https://www.census.gov/geographies/reference-files/time-series/geo/relationship-files.2020.html#zcta.

Our second location-based measure comes from Opportunity Insights data, based on work by Chetty et al. (2022).[21] They look at measures of social connectedness among people in different ZIP codes, and correlate this with rates of economic mobility. Following this, we define a target child as living in a high, medium, or low socially connected ZIP code based on the quintile of connectedness in the OI data.

Table 5. Subgroup measures

Measure	Categories	Definition
		Main analysis
Tax unit adjusted gross income during the baseline year (TY 2019)	Low	Under $30K
	Middle	$30-60K
	High	Over $60K
		Additional subgroup analyses
Subgroup analysis 1: Analysis by race		
Race (as proxied based on the measure of race for the primary filer linked to target child during the baseline period)	Asian	Proxy for target child identified as non-Hispanic Asian
	White	Proxy for target child identified as non-Hispanic white
	Black	Proxy for target child identified as non-Hispanic Black
	Hispanic	Proxy for target child identified as Hispanic
Subgroup analysis 2: Analysis by CDC Social Vulnerability Index of 2020		
CDC Social Vulnerability Index of 2020	High vulnerability	Census tract scores in highest quintiles of the summary vulnerability indicator
	Medium vulnerability	Census tract scores in middle three quintiles of the summary vulnerability indicator
	Low vulnerability	Census tract scores in bottom quintile of the summary vulnerability indicator
Subgroup analysis 3: Analysis by Social capital measure of economic connectedness		
Social capital measure of economic	Low	Bottom quintile in economic connectedness (`ec_zip`) in friendships between low-SES and high-SES individuals living in a given zip code

[21] Chetty, Raj, Matthew O. Jackson, Theresa Kuchler, Johannes Stroebel, Nathaniel Hendren, Robert B. Fluegge, Sara Gong, et al. "Social Capital I: Measurement and Associations with Economic Mobility." *Nature* 608, no. 7921 (August 2022): 108–21. https://doi.org/10.1038/s41586-022-04996-4.

connectedness[22]	Medium	Middle three quintiles in economic connectedness (`ec_zip`) in friendships between low-SES and high-SES individuals living in a given zip code
	High	Highest quintile in economic connectedness (`ec_zip`) in friendships between low-SES and high-SES individuals living in a given zip code

Outcomes

We measure outcomes that capture behaviors of the target child (rather than the tax unit). We use tax data and imported data from IPEDs to generate these outcomes. Our analysis mostly examines the effects of eligibility for the tax benefits on college enrollment outcomes, but also includes measures that capture labor market participation and tax filing behaviors. We describe our planned outcomes in greater detail in Table 6.

Families received larger tax returns around March 2022 and advanced payments in July - December 2021 as a result of the Child Tax Credit of 2021. This time period coincides with when the majority of children in our sample were seniors in high school. If these students decided to enroll in college, they would have applied to colleges when these payments were distributed and made a decision of where to enroll during this period or shortly after.

Our primary outcome year is tax year 2022. Since academic years typically go from August - May and tax years go from January - December, our analysis of college enrollment using TY 2022 is identifying enrollment during the fall 2022 term, the term immediately following high school completion for the majority of students in our sample who graduated high school.

Data on college characteristics will be imported from IPEDs. It will be linked to colleges using the college's Employer Identification Number (EIN) that is found on Form 1098-T.

Table 6. Outcomes

Outcome all for TY 2022	Definition
Primary outcomes	
Child has 1098-T, enrolled at least half-time	1 - Form 1098-T issued by any college or university listing the child's TIN as enrolled at least half-time 0 - otherwise
Child filed a tax return or claimed as a dependent	1 - Child filed tax return as independent tax filer or claimed as a dependent

[22] More information about this data source, including links to the data codebook, and academic papers, including Chetty et al., (2022) can be found on the Opportunity Insights webpage: "Social Capital I: Measurement and Associations with Economic Mobility.

	0 - otherwise (e.g., non-filer)
Secondary outcomes	
Child has 1098-T from a four-year college, enrolled at least half-time	1 - Form 1098-T issued by a four-year college or university listing the child's TIN as enrolled at least half-time 0 - otherwise
Child has 1098-T from a two-year college, enrolled at least half-time	1 - Form 1098-T issued by a two-year college or university listing the child's TIN as enrolled at least half-time 0 - otherwise
Child filed own tax return	1 - Form 1040 with the child's TIN listed as the primary filer or secondary filer; 0 - otherwise
Child claimed as a dependent	1 - Form 1040 with the child's TIN listed as claimed as a dependent; 0 - otherwise
Child is working	1 - W-2 or 1099-NEC issued by any employer listed the child's TIN and income reported > $0 0 - otherwise
Child is working or in school	1 - Child is enrolled in college (primary outcome) or child is working; 0 - otherwise
Other outcomes and robustness checks	
American Opportunity Tax Credit claimed by the child	1 - American Opportunity Tax Credit claimed by child (or on their behalf when child claimed as a dependent) for an amount > $0 0 - otherwise (includes non-filers)
Child enrolled in higher education at least half-time, based on 1098-T data or claiming AOTC	1 - Form 1098-T issued by any college or university listing the child's TIN as enrolled at least half-time or claimed the American Opportunity Tax Credit (AOTC) 0 - otherwise
Child has 1098-T enrolled in higher education, including less than half-time	1 - Form 1098-T issued by any college or university listing the child's TIN in TY 2022 0 - otherwise

Measures of college quality from IPEDS data linked to college EIN where child enrolled at least half-time (using IPEDS data from 2019)	• "college ipeds grad-rates": 150% of regular time completion rates • "college ipeds grad-rates-pell": 150% of regular time completion rates for Pell recipients To account for the fact that some target children will not enroll in college and have a missing value for these measures of college quality, we plan to derive two categorical measures from each of the two continuous IPEDs graduation rate measures as follows: 1 If a graduation rate is above the median graduation for college of the same type (2-year or 4-year); 0 otherwise (including target children who are not enrolled).

Depending on the findings for TY 2022, we may also explore outcomes in later tax years. However, for lower-income portions of our sample EITC eligibility rules may introduce bias into our analysis for outcomes in TY 2023 and beyond (see below).

Planned robustness checks

Robustness checks for sample specification

Sensitivity to predicted income eligibility

- A regression that includes target children, regardless of their family income or whether they were claimed as a dependent.
- Analysis that interacts eligibility with a continuous measure for adjusted gross income (AGI).
- Analysis that defines low-income, middle-income, and high-income using a data driven approach where low-income tax unit is defined as the bottom quintile of AGI, middle income tax unit is defined as the middle 3 quintiles of AGI, and high-income tax unit is defined as the top quintile of AGI.

Sensitivity to bandwidth for date of birth

- Analysis that includes wider birth range bandwidths.
- Analysis that changes the number of days excluded around January 1, 2004.

Sensitivity to state at school entry

- Analysis that includes children who we identify as living in California and Michigan at the point of school entry.

- Since we may be concerned that children living in states excluded at school entry will have few in-migrants during the baseline period, we will run a robustness check that excludes fixed effects for states with school entry dates around the cut off.
- Analysis that excludes children who we identify as living in states that determine school entry by school districts.[23]

Sensitivity to eligibility rules for state implement Child Tax Credit programs

- While our measure for eligibility for tax benefits should take into account state implemented tax benefit programs that use the same cut off, we plan to do a robustness check that drops children living in states during the baseline period that use the same cutoff for eligibility for state implemented Child Tax Credit programs. This includes children living in Arizona, Idaho, Maine, New York, and Oklahoma.[24]

Robustness checks to selection of covariates or covariate definitions

- A regression that includes children who are never claimed as a dependent during the baseline period.
- A "covariate imputed" regression that includes missing data indicators for covariates that rely on Form 1040 information for children who are not claimed as dependents during the baseline years (TY 2019 - 2017). For covariates defined using information returns, we plan to use information for the tax unit linked to the child during the early childhood period.
- We will vary the threshold we use to convert the predicted probabilities of membership in a particular racial/ethnic group to the binary indicator of group membership. While the main analysis uses a 0.75 threshold, we will examine the sensitivity of the subgroup analysis to thresholds of 0.6 and 0.9.

Limitations, additional considerations, and exploratory analysis

Earned Income Tax Credit and Child Tax Credit in infancy

Many researchers have documented the long-term benefits of early investments on lifetime earnings and academic success. Most relevant to the current evaluation comes from Barr et al. (2022) who documented effects of being eligible for additional tax benefits in the first year of life on these longer-term outcomes.[25] This is a limitation and feature of our analysis, because the timing of when families receive these first tax benefits (at around 4 months of age versus 15 months of age) also uses the end of year (January 1, 2004) age cut off used to determine eligibility for the Child Tax Credit of 2020 and 2021. The majority of tax benefits for claiming young children as dependents come from the Earned Income Tax Credit (EITC) that is available to low-income

---

[23] Note that we are separately looking into the school entry rules for this time period for New York City schools. If we learn that they have school entry cut offs near our tax benefit eligibility cut off, we will exclude children living in New York City from our primary sample model.
[24] https://www.ncsl.org/human-services/child-tax-credit-overview.
[25] Barr, A., Eggleston, J., & Smith, A. A. (2022). Investing in infants: The lasting effects of cash transfers to new families. *The Quarterly Journal of Economics*, *137*(4), 2539-2583.

earners only and the Child Tax Credit (CTC) that is available to low-income earners as well as moderate- and high-income earners.

We account for these early payments by running exploratory analysis where we split our sample into tax units who we predict to be below the income-threshold to be eligible for EITC and those who predict were not income eligible. We plan to use the follow procedure to predict eligibility:

1. Identify the primary and if applicable secondary filer linked to the target child during the early childhood period.
2. Predict their eligibility for EITC in 2003 using the following information:
    a. Family structure based on information from 1040 filed in the year the target child was linked to a tax unit during the early childhood period. Note that we'll adjust the ages for children claimed as dependents to their ages in 2002, with the exception that we'll assume all families have at least one child (i.e., the target child) for EITC eligibility purposes.
    b. Information returns from the primary (and if applicable) secondary filers in TY 2002.

We run analysis for each of these groups separately to answer slightly different research questions described below:

- While eligibility for EITC in TY 2003 is a limitation of our analysis for isolating the effects of the Child Tax Credit of 2020 and 2021, it also becomes a feature of our data when we consider a different research question on when during the life course do investments matter and when do they matter most. By limiting the sample to those eligible for EITC during infancy, we set up a direct test (or "horse race") between the effect of investments in the first months of life compared to the effects of liquidity when making college choice decisions on low-income children's college enrollment decisions.

- By limiting our sample to tax units who are too high income to be eligible for EITC, the slightly older children do not get additional benefits from EITC than the slightly younger children during infancy. This allows us to better isolate the effects of eligibility for the Child Tax Credit of 2020 and 2021 from the effects of eligibility for EITC during childhood. However, given the higher-income threshold for the Child Tax Credit of 2003, we do not limit our sample further based on income eligibility and instead acknowledge that eligibility for these benefits in infancy could be a source of bias in our results, even among this higher income group.

If we are able to obtain additional data, we also plan to include placebo years in our analysis to help disentangle the effects of the eligibility for different benefits and the timing of when children and their families would receive these benefits. To do so, we would use data from two placebo years, in which children are born in years that are ***<u>not</u>*** used for age-based eligibility cut offs for Economic Impact Payments (EIPs) or the Child Tax Credit of 2020 and 2021. These years are:

- Placebo cohort 1: born around the threshold of January 1 2002 - High school class of 2020

- Placebo cohort 2: born around the threshold of January 1 2005 - High school class of 2023

In these placebo years, children born in December and January are both eligible to be claimed as dependents for the purposes of EITC and the Child Tax Credit for the same number of years; however, the timing of when these benefits are made differ. The children born in December are first eligible to receive tax benefits a few months after they are born whereas children born in January must wait until the following tax year. In contrast, children born in December are eligible for their last year of benefits approximately a year before children born in January.[26] In placebo cohort 1, the children were too old to be eligible to be claimed as dependents for EIPs or the Child Tax Credit of 2021. In placebo cohort 2, the children were eligible to be claimed as dependents for EIPs and the Child Tax Credit of 2021, but would have received these benefits before the sensitive period when they were making college choice decisions.

The focal cohorts are the same as the placebo cohorts in that the timing of their first and last year of benefits as a dependent depends on whether the child is born in December or January. The focal cohorts differ from these placebo cohorts in that none of the members of these placebo cohorts are eligible for additional tax benefits when they are making college choice decisions. Including these additional cohorts in our analysis, should help us disentangle the effects of payment timing from the effects of eligibility for additional benefits.

Complier effects

The main analysis is an ITT specification focused on children who are likely eligible for the Child Tax Credit of 2020 and 2021. If feasible, we plan to conduct an exploratory analysis that examines the impact among compliers, or target children in the sample who, in addition to being eligible for the credit, received it. To do so, we will use the following definition of "receipt of benefit" that we will construct for research question one, defining all target children with non-zero receipt as compliers: "Search for the tax unit linked to the target child in tax year 2020 and 2021 to report actual tax credit benefit receipt in these years for the target child."

We will then repeat the specification for Research Questions 2-5 but use the two-staged least squared approach to analyzing compliance—fit a first stage regression predicting receipt of the benefit using the same covariates as in the main analysis and then using the fitted values (and appropriate standard error correction) to analyze the impact on compliers.

Other tax benefits using same age cut off

While the slightly older children are not age eligible for the Child Tax Credit of 2020 and 2021, they are eligible to be claimed as a dependent for the purposes of the Other Dependents Tax Credit. Eligibility for the benefit may offset some of the effect of eligibility for the Child Tax Credit of 2020 and 2021. Additionally, certain states also have state-level CTCs which use the same age

[26] In most tax years, children must be under age 19 (under age 17) at the end of tax year to be claimed for the purposes of EITC (CTC).

cutoff (Arizona, Idaho, Maine, New York, and Oklahoma).[27] Thus we cannot attribute any impacts on our outcome variables entirely to the Child Tax Credit of 2020 and 2021. However, we plan to account for this limitation by presenting information on the actual difference in benefit receipt and after-tax income.

1098-T Form coverage

In some cases, schools and universities may not provide the 1098-T Form to enrolled students (see Cronin & Gray-Hancuch, 2024 for a discussion).[28] This happens when the students pay for college entirely through grants. Since in these cases the student does not owe tuition and fees, colleges are not required to report the Form 1098-T to the student or the IRS and only some choose to do so. This most often occurs among two-year community colleges where Pell Grants are more likely to cover the full cost of tuition and fees. This occurs both because tuition and fees are low and students at these schools, who are often low income, are more likely to qualify for Pell Grants.

This missing data problem could introduce bias if eligibility for the tax benefits changes the types of college in which students apply and enroll. For example, consider a child who would enroll in a two-year community college without the additional income, but would enroll in a four-year college with the additional income. In this case, they would only be linked to a 1098-T Form when enrolled at the four-year college. That is we would underestimate enrollment in two-year colleges and be more likely to do so when the target child was not eligible for additional funds. In this scenario, we would differentially observe outcomes on college enrollment for those who are eligible for benefits compared to those ineligible for tax benefits.

We plan to account for this limitation by:

- Including take-up of higher education tax credits as part of our measure for college enrollment, since families can take-up these benefits even if they do not have a Form 1098-T;
- Examine the effects on enrollment in four-year college, where grants are less likely to cover the full cost of college;
- Examine the effects among children from middle- and high-income families who are less likely to have the full cost of tuition covered by grants; and
- (if feasible) run robustness checks where we limit our sample to students living in states where colleges appear to report Form 1098-T data for all students, even for students who owe no tuition and fees.

TY 2023 and beyond

Qualifying child eligibility rules for the purposes of the Earned Income Tax Credit include that the child needs to be under age 19 at the end of the tax year or under age 24 at the end of the tax year and a full-time student for at least five months of the year. While all of the children in our sample

[27] https://www.ncsl.org/human-services/child-tax-credit-overview.
[28] Cronin, J. A., & Gray-Hancuch, J. (2024). *Barriers to Claiming Education Tax Credits for Low-Income Students* (Working Paper 125). Office of Tax Analysis, U.S. Department of Treasury. https://home.treasury.gov/system/files/131/WP-125.pdf.

meet the requirement of under age 19 in TY 2022, they would not meet this requirement in TY 2023 and later. Thus, for the full sample, examining the effects of eligibility for the Child Tax Credit of 2020 and 2021 on continued enrollment after TY 2022 could be picking up the effect of eligibility for this program. One approach that could circumvent this issue is to limit the sample to tax units unlikely to be eligible for EITC (i.e., middle and higher income families) or limit the sample to families where three or more other children in the household are younger than the target child.

Analysis Plan

Project Name: Examining the impacts of the COVID-era direct payments during the transition to adulthood - Economic Impact Payments

Project Code: 2312

Date Finalized: 1/3/2025

The content of this document does not necessarily reflect the views or the official positions of the U.S. Department of the Treasury or the Internal Revenue Service and has been reviewed to ensure that no confidential information is disclosed.

In-document links

Project description

In 2020 and 2021, the Internal Revenue Service (IRS) issued $837 billion dollars in direct payments to individuals to reduce financial stress brought on by the COVID-19 pandemic. The Economic Impact Payments (EIPs, colloquially known as the stimulus checks) were the largest stimulus payments made to individuals in recent history and income eligibility for these payments was nearly universal.[1] Our research seeks to understand the impact of eligibility for these pandemic-era payments on key outcomes for adolescents. By mitigating the negative economic impacts of the pandemic, these tax benefits may have impacted the choice sets faced by teens and their families. We are primarily interested in examining impacts on college enrollment decisions, but will also examine tax filing behaviors and labor market participation in the years following the payments.

Our evaluation of the impacts on adolescents of eligibility for the EIPs uses individual-level tax records and a regression discontinuity evaluation design. The discontinuity used to evaluate the effects of these benefits is based on the adolescents' dates of birth, which partially determined eligibility for these tax benefits. Specifically, families with qualifying dependents aged 16 or younger as of the end of 2019 could claim up to $1,100 in EIP funds from the first two stimulus payments, in addition to the funds the parents were eligible for. We compare outcomes for teens who fall just below this age cutoff, to otherwise-similar teens who fall just above this cutoff, to determine the causal impacts of being eligible to receive these additional funds.[2]

We also will examine the extent to which the impacts of eligibility for the EIPs differ for different taxpayer segments, including socially disadvantaged communities or groups that have experienced systemic discrimination.

Learnings from this evaluation will support the strategic priorities of the IRS to better understand tax filing behaviors to improve tax administration and to understand how existing tax policy affects people and the economy. We are conducting this project as part of the Joint Statistical Research Program, a program within the IRS that provides researchers with access to tax microdata. This project is also part of the Office of Evaluation Sciences' portfolio of research on pandemic relief and economic recovery.

This Analysis Plan will be posted on the OES website at oes.gsa.gov before outcome data are analyzed.

Research questions

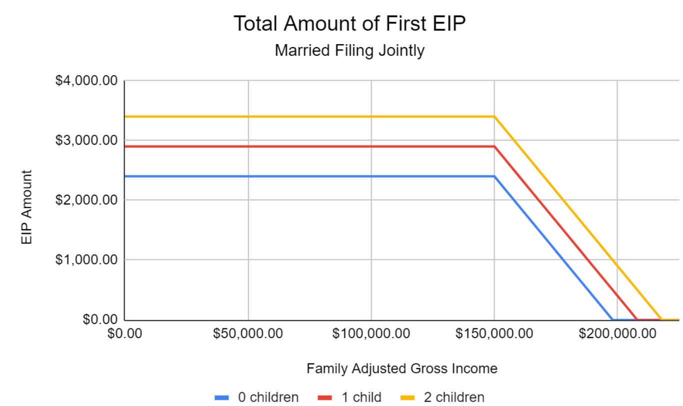
Our primary research question looks at the impacts of eligibility for the EIPs on college enrollment. We are also interested in tax filing behaviors and employment. We will employ an intent-to-treat analysis; that is, we look at the impacts of eligibility for the EIPs; we do not currently plan to look at the impact of receipt of the EIPs due to concerns about our ability to accurately identify payment receipt (described in more detail below).

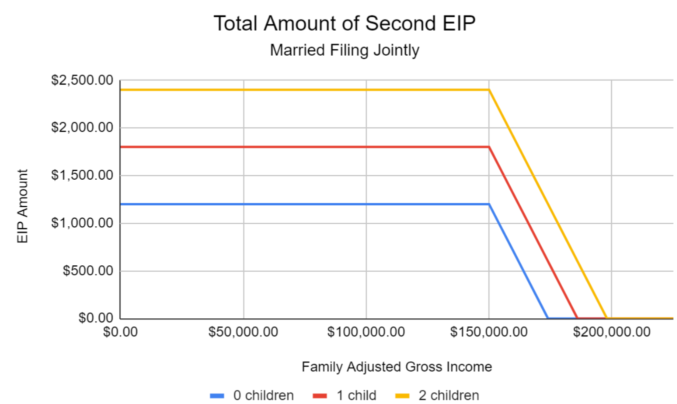
Importantly, most families were eligible for some level of EIP funding. The figures below show the amounts families were eligible for by income, if married filing jointly (income thresholds are different for those filing as single or head of household, but the graphs of their benefit amounts have the same shape). All adults making under $75,000 per year, or $150,000 if married filing jointly, were eligible to be sent $1,200 per adult plus $500 per qualifying child for the first EIP,

[1] Stimulus Checks: Direct Payments to Individuals during the COVID-19 Pandemic | U.S. GAO.

[2] As described in further detail below, the age cutoff for a qualifying dependent for EIPs is the same as for the Child Tax Credit of 2019. Thus, our analysis will measure the impact of eligibility for both payments.

issued in April of 2020, and $600 per adult plus $600 per qualifying child for the second EIP, issued in December 2020/January 2021. Thus our research focuses on the impact of the additional funding a family was eligible for if they had a child just under the upper age limit, relative to a family with a child just over the age limit. To illustrate, consider a family with two parents and two children, ages 12 and 16 as of the end of 2019, with income below $150,000. Their total payment for the first EIP will be $3,400 ($1,200 x 2 adults + $500 x 2 children), and their total payment for the second EIP will be $2,400 ($600 x 2 adults + $600 x 2 children). The relevant counterfactual is an otherwise identical family where the older child is 17 and thus no longer qualifies, meaning that the family is only eligible for $2,900 for the first EIP and $1,800 for the second EIP. We look at the impact on that child's outcomes of the family's eligibility for the additional $1,100.





We note, however, that the same eligibility cutoff applies for claiming dependents for the federal Child Tax Credit for tax year 2019 (in spring of 2020), as well as certain state-level child tax credits (depending on the state), so we are not able to disentangle the impacts of the two programs. We discuss this limitation and our plans to address it in further detail below.

Before we conduct our planned analysis of the causal effects of eligibility for the EIPs, we will conduct two additional sets of analyses. This preliminary analysis intends to provide evidence on the credibility of our identification strategy (evaluation design) and evidence of what the treatment that we evaluate is in practice.

Our preliminary analyses seek to answer the questions:

P1. What is the relationship between eligibility for the Economic Impact Payments as a qualifying child[3] and receipt of EIPs (or after tax income)?

P2. What evidence supports (or discredits) the idea that families with slightly younger or older children are similar to one another based on observable characteristics?

Next, we turn to our causal research questions. Our primary (main) research questions are:

[3] This is defined in the Sample Identification section, below.

M1. What is the effect of eligibility for the Economic Impact Payments as a qualifying child on college enrollment in 2021 for adolescents from low-, middle-, and high-income families?

M2. What is the effect of eligibility for the Economic Impact Payments as a qualifying child on how an adolescent appears on the tax return in 2021; i.e. whether they are claimed as a dependent or file their own return, among adolescents from low-, middle-, and high-income families?

Our secondary research questions look at whether eligibility for the EIPs as a qualifying child impact:

S1. The type of college (two-year or four-year) in which the adolescent enrolls?

S2. Adolescents' likelihood of working or being enrolled in college?

S3. The quality of the college in which the adolescent enrolls?

Finally, we look at whether the impacts of eligibility for the EIPs on our two primary outcomes differ for children who are members of socially disadvantaged communities or groups that have experienced systemic discrimination. We describe how we operationalize this definition below.

Data sources

This analysis will use centrally housed and de-identified administrative data maintained by the Internal Revenue Services (IRS) to meet the needs of research analysts.[4] We describe the data sources in additional detail in Table 1.

Most of our analysis uses administrative data that are reported to the IRS on behalf of individuals. Regardless of whether an individual files their taxes, employers, colleges, government agencies, and other entities share data on the individual with the IRS for the purposes of tax administration. These data include forms such as the W-2 or 1099 (for wages and taxes withheld) and 1098-T (for reporting higher education expenses), among others, that are known as "information returns." The Social Security Administration (SSA) also shares data on individuals' dates of birth and death with the IRS.

In addition, taxpayers share self-reported information with the IRS that often is not captured in other administrative data sources. Self-reported data are reported to the IRS only when individuals file their taxes and complete a specific form. The main reason we use self-reported data is to link children to tax units, which could be thought of as the child's family. Tax units include primary filers, secondary filers when a married couple files jointly, and children who are claimed as dependents. The self-reported information used to define tax units is captured in the Form 1040.

For our heterogeneity analysis, we link the adolescent's location to data at the census-tract and zip-code levels that defines vulnerability to shocks or social disadvantage at the community level.

[4] The IRS provided data access to do this analysis and reporting on the findings as part of the 2023 Statistics of Income Joint Statistical Research Program (JSRP).

These data come from the Centers for Disease Control Social Vulnerability Index (SVI) and from Opportunity Insights, and are described in more detail in the section on heterogeneous treatment effects, below.

In addition to heterogeneity in social disadvantage at the community level, we intend to look at heterogeneity by (predicted) race. We do not directly observe race or ethnicity for the children in our sample. Instead, we will make use of race and ethnicity imputations already generated by the IRS. Again, this is described in more detail in the section on heterogeneous treatment effects, below.

Finally, we use publicly available data from the Integrated Postsecondary Education Data System (IPEDS), which includes information on colleges, including college type (i.e., 4-year or 2-year), graduation rates, acceptance rates, tuition and fees, among many other measures. For children who enroll in college, we link this information to the child using the Employer Identification Number (EIN) for the school listed on the Form 1098-T that the college issues to the child.

Table 1. Data sources for examining the effects of eligibility for the first and second Economic Impact Payments as qualifying dependent

Data source	Description	Primary use
Social Security Administration Birth Records, shared with IRS for purposes of tax administration	All births and people issued Social Security Numbers that are shared with the IRS for purposes of tax administration.	Define sample.
Form 1098-T: Tuition Statement	An information return that a college or university sends to the IRS for enrolled students.	Measure college enrollment outcomes.
IPEDS: Integrated Postsecondary Education Data System	Publicly available data on college characteristics maintained by the U.S. Department of Education	Measure characteristics of colleges where students enrolled.
Form 1040: U.S. Individual Income Tax Return	A form that a taxpayer provides when filing their taxes. Used to claim children as dependents, list amounts of income from different sources, claim tax benefits, and determine amount of tax due/refund owed.	Used to link children to tax units, refine the analytic sample, to include measures of family characteristics as covariates, and use these measures to assess the validity of the quasi-experimental evaluation design.

Form W-2: Wage and Tax Statement	An information return on wages that an employer sends to the IRS for their employees.	Used to measure income and predict eligibility for the tax benefit. Used to measure work force participation as a covariate and outcome of interest for the target children.
Form 1099-NEC: Non-Employee Compensation	An information return on compensation that an employer sends to the IRS for their contractors.	
CDC/ATSDR Social Vulnerability Index (CDC/ATSDR SVI)	Census tract-level indicators of social vulnerability/disadvantage.	Define subgroups for heterogeneity analysis.
Opportunity Insights	Census tract-level indicators of social capital and mobility.	Define subgroups for heterogeneity analysis.
IRS imputations of individual race and ethnicity	Probability score of race and ethnicity based on name and location.	Define subgroups for heterogeneity analysis.

Sample identification

Our study sample includes individuals who were born in 2002-2003 and are expected to graduate high school in the spring of 2021, such that their college decisions coincide with the timing of the EIPs. We then associate these individuals with their and their parents'/guardians' tax returns and other tax records maintained by the IRS.

Families with qualifying children ages 16 and under as of the end of 2019 were eligible for up to an additional $500 in benefits per child distributed as part of the first EIP starting in April 2020, and $600 in benefits per child distributed as part of the second EIP starting in December 2020.[5] We therefore propose to examine the combined effect of the first and second EIPs by comparing families with dependents aged 16, who would have been eligible for the additional $1,100 in total benefits, to otherwise-similar families with dependents aged 17, who would not have been eligible for the additional funds.

However, it is also important to note that the Child Tax Credit of 2019 used the same age eligibility criteria as the EIPs to claim a qualifying child. Thus, the families with slightly younger children were eligible for up to $2,000 in refundable and non-refundable tax benefits for the Child Tax Credit of 2019. While the families with slightly older children could not claim that benefit, they could instead claim the Credit for Other Dependents of 2019, which provided a maximum benefit of $500 for children under age 18 and offset the benefits provided by the Child Tax Credit. We

[5] There were no age-based eligibility rules for the $1,400 in benefits distributed as part of the third EIP starting in March 2021. Since we are unable to identify the effects of these payments, they are excluded from our causal analysis.

discuss this limitation and our rationale for focusing on after-tax income to model eligibility and family liquidity during the college choice process in greater detail below.

In addition to being under the age limit, a qualifying child is one who lives with the person claiming them for more than half the year, and is the claimant's child, stepchild, eligible foster child, sibling, grandchild, niece, or nephew. The child must be a US citizen, permanent resident, or other qualifying resident alien, and must have a Social Security Number valid for employment or an Adoption Taxpayer Identification Number.[6] We thus start identifying our sample of potentially eligible children using Social Security Administration (SSA) records of birthdates for all individuals who have valid Social Security Numbers (SSNs) and were born between October 1, 2002 and March 31, 2003. We drop children from our sample who have a date of death on or before December 31, 2018 (the end of our baseline year; more on this definition below). When a child has more than one date of birth (DOB) or date of death (DOD) in the data (usually due to a clerical error that is later corrected), we drop that child from the sample. This forms our full sample of what we refer to as "target children" below.

Following work by Barr et al. (2022)[7] and Lippold and Luczywek (2023),[8] which use a similar age eligibility regression discontinuity design, for our primary analyses we limit the sample of qualifying children to those born within a 31 day window of January 1, 2003 (i.e., December 1, 2002 - January 31, 2003, inclusive). This is intended to ensure that the sample of treated and comparison children are similar on all observed and unobserved characteristics, except for assignment to the EIP "treatment." Additionally, a key assumption underpinning the validity of our regression discontinuity design is that individuals just under or over the discontinuity either don't know about the cutoff in the running variable, or that there is no action they can take that would move them above or below this cutoff. If this does not hold, then there may be selection into treatment, violating the assumption of independence between treatment assignment and potential outcomes. In our case, the birthdate cutoffs were public information, so families could have known about them. It is true that there is nothing a tax filer could have done to change their child's birthdate in order to qualify for more funds (short of lying, which is irrelevant in this context since we rely on SSA data for our birthdate variable); however, there is evidence that parents can and do schedule inductions or c-sections to avoid their child being born on Christmas or New Year's.[9] While this would not imply direct selection into treatment (since it would have occurred 17 years prior), it could lead to imbalances in covariates associated with outcomes, if better-resourced families are more likely to choose to change their child's birthday. To avoid this, again following Barr et al. (2002), we exclude from our sample children born within 8 days of January 1 (i.e., we run a "donut" RD, excluding children born December 24, 2002 - January 8, 2003,

---

[6] https://www.irs.gov/newsroom/calculating-the-economic-impact-payment.

[7] Barr, Andrew, Jonathan Eggleston, and Alexander A Smith. "Investing in Infants: The Lasting Effects of Cash Transfers to New Families." *The Quarterly Journal of Economics* 137, no. 4 (November 1, 2022): 2539–83. https://doi.org/10.1093/qje/qjac023.

[8] Lippold, Kye, and Beata Luczywek. "Estimating Income Effects on Earnings Using the 2021 Child Tax Credit Expansion," September 29, 2023. https://beata-luczywek.com/files/Luczywek_JMP.pdf.

[9] LaLumia, Sara, James M. Sallee, and Nicholas Turner. "New Evidence on Taxes and the Timing of Birth." *American Economic Journal: Economic Policy* 7, no. 2 (May 2015): 258–93. https://doi.org/10.1257/pol.20130243.

inclusive). We will check the robustness of our results to changes in both the selection of window size and donut size (robustness checks described below).

We expect children in this sample to be seniors in high school in academic year 2020-2021, so the families of those who are eligible to be claimed as dependents received extra EIP funds in the spring of the child's junior year and fall of the child's senior year, in time for making key college decisions. It is also crucial for the validity of our regression discontinuity design that older children not be systematically in a different grade than younger children.[10] The tax data do not contain information on the child's grade level in school. We thus proxy for grade using age, but, importantly, we exclude children from the sample if, at age 5, they were living in a state that used a cutoff date for earliest kindergarten start that falls within the range of dates that we use as our running variable. To clarify, consider two children. Adrian was born Dec. 15, 2002, and Barbara was born Jan. 15, 2003. Adrian and Barbara live in a state where the law requires that children have turned age 5 by October 1 of a given year in order to start kindergarten in that year. Thus the earliest year Adrian and Barbara can start kindergarten is fall of 2008 (since both were born after the cutoff for starting in 2007). However, if they live in a state where the law states that children must have turned age 5 by December 31 of a given year in order to start kindergarten that year, then Adrian can start in fall of 2007, while Barbara must wait until fall of 2008, in which case they will be in different grades. We therefore exclude from the sample children living in California (where children must turn 5 by December 2), Connecticut (January 1), Hawaii (January 1), Michigan (December 1), Vermont (January 1), and Washington, DC (December 31). An additional five states leave the kindergarten start date cutoff up to the Local Education Authority (LEA, aka school district: Colorado, New Hampshire, New Jersey, New York, and Pennsylvania).[11] We include children living in these states in our sample, but will run a robustness check in which we exclude them.[12]

In order to identify where children were living when they were eligible to start kindergarten, we search for all the children in our sample among SSNs of dependents claimed on tax returns (Form 1040) in tax year (TY) 2007 (filed in spring of 2008, when all the children in the sample would have turned 5 and just before they would have started kindergarten in fall 2008). We link these children to their parent(s)' or guardian(s)' SSN(s). If we cannot find the child in TY 2007 (i.e., they were not claimed as a dependent in TY 2007), we look in TY 2006, then 2005, then 2004, and finally 2003 (the first year after birth when all of the children could have been claimed as dependents). We exclude from the sample children who were never claimed as dependents in tax years 2003-2007, as we cannot link them to a parent or guardian. We also exclude from the sample children who, in

---

[10] See Angrist, Joshua D., and Alan B. Krueger. "The Effect of Age at School Entry on Educational Attainment: An Application of Instrumental Variables with Moments from Two Samples." *Journal of the American Statistical Association* 87, no. 418 (June 1, 1992): 328–36. https://doi.org/10.1080/01621459.1992.10475212 and Bedard, Kelly, and Elizabeth Dhuey. "School-Entry Policies and Skill Accumulation Across Directly and Indirectly Affected Individuals." *Journal of Human Resources* 47, no. 3 (July 1, 2012): 643–83. https://doi.org/10.3368/jhr.47.3.643.

[11] Note that we are separately looking into the school entry rules for this time period for New York City schools. If we learn that they have school entry cut offs near our tax benefit eligibility cut off, we will exclude children living in New York City from our primary sample model.

[12] https://www.ecs.org/clearinghouse/73/67/7367.pdf; https://www.ecs.org/clearinghouse/78/60/7860.pdf. Note that Massachusetts also leaves the kindergarten start date cutoff up to the LEAs, but all the MA LEAs have cutoff dates outside of our birth date window: https://www.doe.mass.edu/sfs/earlylearning/resources/entry.aspx.

the most recent year in which we find them claimed as a dependent, were claimed on more than one tax return. Dual claiming like this technically is not legal, but can happen if, for example, the child's parents are divorced and both claim the child on their returns. After linking the child to at least one parent or guardian, we pull the address information for that parent or guardian from the parent's Form 1040 in the year they are most recently linked to the child.

Looking at birthdates and child's location assumes that all children in the same place at the same age start school at the same time and progress through at the same pace. This will not hold true if the child is in a private school system which does not follow the same dates, is home schooled, or is skipped ahead or held back a grade. However, since we cannot observe these individual-level differences in grade level, we consider our approach to be an appropriate proxy. Further, we do not have reason to believe that the children on either side of the discontinuity would be differentially likely to be in different grades due to these reasons.

Next, we link the child to a tax unit in a "baseline" year just prior to when the child's family would have received the EIPs. The tax unit for this study consists of the child's parent(s) or guardian(s) who claim the child as a dependent, plus any other dependents also claimed on the same return. Some adolescents may file their own return and not be claimed as a dependent by their parents (e.g. if they have already moved out and potentially married or had their own children). Children (of any age) may also file their own tax returns if they have their own income, regardless of whether they are also claimed as dependents on their parents' return. We exclude from our sample children who file their own return and who are not also claimed as a dependent on a parent's return, as they could have been sent the EIPs as adults rather than as qualifying children and thus would not have been subject to the age cutoff that we use for our identification.[13]

We use the tax unit in the baseline year for two key components of our analysis. First, we use tax data on income and number of dependents claimed to predict the amount of EIP funding the family was eligible to receive and exclude children from the sample whose family income was too high to be eligible. As described above, depending on filing status and number of dependents, the EIP benefit begins to phase out at a family adjusted gross income (AGI) of $150,000 (for married filing jointly, $75,000 for single filing status), and falls to zero at a family AGI of around $200,000. We include children whose family AGI falls in the phase-out region, but exclude those whose family AGI is too high to receive any EIP. Second, we use the data from the tax unit to define covariates and subgroups for our heterogeneity analyses (described below).

In determining the actual EIP amounts due to families, the IRS used the 2019 return (filed in spring 2020). The first of the EIPs was distributed to most taxpayers by April 15, 2020, but the tax filing deadline in that year was extended to July 15 due to the pandemic. Thus individuals could have known about the EIP eligibility rules prior to filing. This means that for tax year 2019, the choice to file, how much income to report, and whether and how to claim dependents, is endogenous.

[13] Individuals were not eligible for the EIPs as independent adults if they qualified to be claimed as a dependent on someone else's return, regardless of whether they actually were claimed or not. The Form 1040 does include a checkbox for whether the taxpayer or their spouse can be claimed as a dependent on someone else's return. However, we opted to exclude all children who filed their own return and were not claimed as dependents, rather than just those who did not check this box, as the data from that checkbox does not appear to be consistently reported.

Additionally, the older children in our sample would not have been eligible to be claimed as qualifying children in 2019, and thus we are less likely to be able to link them to a tax unit. For these reasons, we use TY 2018 (or earlier) as our baseline year for linking the child to a tax unit.[14]

Specifically, we look in the tax data for any return that was filed on which the child's TIN was listed as a dependent in TY 2018, and we link them to the TIN of the primary filer (and secondary, if married filing jointly). We also look for returns on which the child's TIN is primary or secondary. If the child's TIN is not found in 2018, we search in TY 2017, and then in TY 2016 if still not found. This limits our sample to families who filed a tax return claiming the dependent at least once in 2016-18, which likely skews higher income, as lower income people are not required to file. In robustness checks (described further below), we plan to run models which are not limited in this way. We exclude from the sample children who, in the most recent year in which we find them claimed as a dependent, were claimed on more than one tax return, as we want to link each child to only one tax unit. We also exclude children from the sample if, in any year from 2016-2018, the child files their own return and is not also claimed as a dependent on someone else's return (due to the EIP eligibility restrictions described above).

To determine (likely) eligibility for the EIPs, we pull the filing status and number and ages of all dependents (adjusted to their age as of Dec. 31, 2019, with the exception of the target child, who we assume to be age-eligible in order to not exclude our comparison group from the sample) in the tax unit as of the most recent year (of 2016-2018) in which the index child was claimed as a dependent. If the child was claimed in 2018, then we pull the adjusted gross income (AGI) listed on the tax unit's Form 1040 in TY 2018. If the child was not claimed in 2018, then we use the total income from all Forms W-2 and 1099-NEC issued to the tax unit's primary and secondary filers in TY 2018 to proxy for 2018 AGI (that is, even if the child is not linked to a tax unit in 2018, but is linked to a tax unit as of 2016, we use the 2018 information returns from the primary and secondary filers on that 2016 return). We use the 2018 AGI (or its proxy), plus the most recent information on family structure, to characterize the dollar amount of EIPs that the family was likely eligible to receive. If this value is non-zero, then we will consider the family eligible and will include them (or, more precisely, the target child) in our sample.

A complication with our strategy is that the adult(s) who claimed the child in 2016, 2017, or 2018 may not be the same as the filer who would have received the EIPs on behalf of that child. For example, it is not uncommon for divorced parents to switch off claiming a child for the purposes of tax benefits. In this case, we might classify the child erroneously as being or not being eligible for EIP funds, if we assign the child to the "wrong" tax unit. However, we do not believe this will occur systematically more or less on either side of our regression discontinuity.

[14] Note that if the family had not yet filed their 2019 taxes before the IRS issued the first EIP, the IRS used information from the family's 2018 return to compute the EIP amount. However, we are not concerned about endogeneity of the 2018 filing decision, as the 2018 return would have been filed prior to the creation of the EIPs.

Planned analyses

Primary regression specification

Our empirical model is a regression discontinuity design that leverages the birthdate cutoff after January 1, 2003 to determine the causal impact of eligibility for additional EIP funds on our outcomes of interest. We adopt the local randomization justification for our regression discontinuity, and assume that, within a given window of birthdays around January 1, (in)eligibility for the EIPs is as good as random.[15] Our regression specification is as follows:

$$Y_i = \beta_0 + \beta_1 1[z_i > 0] + \beta_2 z_i + \beta_3 1[z_i > 0] \times z_i + X_i'\gamma + \varepsilon_i$$

(Equation 1)

Where Y_i is an outcome of interest, z_i is the number of days between the child's birthdate and January 1 (centered at zero), and $1[z_i > 0]$ is a binary indicator equal to one if target child *i* is born on or after January 1. X_i is a vector of individual and tax unit covariates, defined below; in some models we may exclude these. The primary coefficient of interest is β_1, which identifies the impact of eligibility for the EIPs (the intent-to-treat estimate).

We implement this model using ordinary least squares regression limited to the relevant window (described above).[16] We use robust standard errors clustered at the level of the tax unit, to account for the fact that some tax units may have more than one child who falls into our sample (e.g., families with twins), in which case outcomes for those children would be correlated. We will use a cutoff of p = 0.05 to determine statistical significance (with stars according to + p = 0.10, * p = 0.05, ** p = 0.01). All tests will be two-tailed.

Since we have one primary outcome in a given domain (college enrollment or tax filing) and are interested in drawing conclusions within different income groups (low-, middle-, and high-income), we do not plan to adjust for multiple comparisons when reporting findings for the OES abstract.[17]

Preliminary Analyses

As described above, prior to conducting our main analysis, we conduct preliminary analyses to provide evidence on the credibility of our identification strategy (evaluation design) and evidence of what the treatment that we evaluate is in practice.

[15] Cattaneo, Matias D., Nicolas Idrobo, and Rocío Titiunik. "A Practical Introduction to Regression Discontinuity Designs: Extensions." *Elements in Quantitative and Computational Methods for the Social Sciences*, March 2024. https://doi.org/10.1017/9781009441896.

[16] Cattaneo et al. (2024) provide packages in R and Stata that implement local randomization regression discontinuity analyses. However, their packages rely on Fisherian inference, in order to be robust to small sample sizes. Given that our sample includes several hundred thousand children, we plan to rely instead on standard inference procedures that are valid in large samples, but will run robustness checks using their package.

[17] Rubin, Mark. "Inconsistent Multiple Testing Corrections: The Fallacy of Using Family-Based Error Rates to Make Inferences about Individual Hypotheses." *Methods in Psychology* 10 (November 1, 2024): 100140. https://doi.org/10.1016/j.metip.2024.100140.

Our preliminary analyses seek to answer the questions:

P1. What is the relationship between eligibility for the Economic Impact Payments as a qualifying child and receipt of EIPs?

P2. What evidence supports (or discredits) the idea that families with slightly younger or older children are similar to one another based on observable characteristics?

P1: What is the relationship between eligibility for the Economic Impact Payments as a qualifying child and receipt of EIPs?

In addition to analyzing the impacts of eligibility for the EIPs, we plan to model the amount of money the family received in tax benefits because of the child. We will use this to construct a "first stage" for our regression discontinuity, showing (hopefully) the existence of a jump in the amount of benefits around the January 1, 2003 birthday cutoff. We plan to do this in a few different ways.

First, as described in the sample selection section above, we plan to use the tax unit's AGI from 2018 (or its proxy constructed from 2018 information returns, for those who did not file), plus the most recent information on the family structure (number of adults and qualifying dependents) to estimate the amount of EIP funds the tax unit would have been eligible to receive.

Second, we will use the same information to model after tax income. We will model this using the TaxSim software provided by the National Bureau of Economic Research.[18] After tax income is important because it takes into consideration other tax benefits that the tax unit may be eligible for. Specifically, the federal Child Tax Credit and some state-level child tax credits use the same age cutoff for eligibility (further information on this is discussed in the Limitations section, below). By looking at the after tax income, we will be able to characterize the size of the income discontinuity generated by all tax benefits, not just the EIPs.

Third, we plan to look at the actual amount of EIP payments sent to the tax unit, using records maintained by the IRS of all payments made to taxpayers. The output of this analysis will include information on the total amount that a tax unit was sent for the adults in the unit, and the total amount sent for dependents.[19] We pull the TINs for the primary and secondary filers from the tax unit associated with the child at baseline (one of 2016-2018, as described above). We then search for those TINs within the data on EIP payment amounts. If found, we pull the information on the total amounts received for adults and dependents. If neither the primary nor secondary filer is found in this data, we code the tax unit as having received $0 in EIP payments.

---

[18] https://taxsim.nber.org/index.html.

[19] We are grateful to William Boning and Kye Lippold for sharing this code with us. This data also includes information on reversals, meaning payments that were returned to the IRS. This occurs when a direct deposit to a taxpayer's bank account cannot be completed because the account is now closed, or when a check issued to a taxpayer is never cashed or is returned to the IRS due to incorrect address information.

For people who were not required to file a tax return or who otherwise did not receive the EIPs automatically[20] (e.g., people whose income falls below the filing threshold), the IRS had two methods by which they could claim their EIPs. First, they could fill out the online “Non-Filers: Enter Payment Info Here” tool.[21] This was available starting in April of 2020, and requested information on the individual’s marital status, dependents, and income. Second, they could claim any missing EIPs (i.e., if they hadn’t received a payment, or had received less than they thought they were due) as a credit on their 2020 taxes (the Recovery Rebate Credit or RRC), if they filed a 2020 return. We expect to be able to find tax units who were sent EIPs after using the Non-Filer tool in the same way as we find them if they filed (described above), as the payments are recorded in the same way. To determine EIP amounts received via the RRC, we will search for the primary and secondary filers in the tax unit among 2020 returns and look at the amount the tax unit was sent as part of the RRC.

A complication with our strategy is that the adult who claimed the child in 2016, 2017, or 2018 (our baseline years) may not be the same as the filer who would have received the EIPs on behalf of that child, e.g., if divorced parents switch off claiming the child for the purposes of tax benefits. In this case, we might classify the child’s tax unit erroneously as having received or not received EIP funds, if we search for the wrong parent in the EIP data. However, we do not believe this will occur systematically more or less on either side of our regression discontinuity.

An additional complication could occur if the child was claimed on a return filed jointly by two parents at baseline, but the parents have divorced in the intervening year(s), and each files their own return in the year that the IRS used for EIP determination (2019 or 2018). To account for this, will look for both the primary and secondary filer TINs in the EIP payment data, and will total the EIP amount sent to both adults and assign that total to the target child.

If the data allows, we will use a second strategy for determining the actual amount of EIP payments. This strategy focuses on finding the target child first, and then linking that child back to a tax unit to determine the amount of EIPs associated with that child. Thus it does not rely on picking a tax unit from prior years and assigning that tax unit to the child, whether or not the child is still in the same tax unit at the time of the EIPs (avoiding the complications described in the preceding paragraphs). However, identifying EIP amounts this way is significantly more complicated and may not be feasible.

For each of these four approaches (modeling EIP amount based on 2018 income and family structure, modeling after tax income based on the same, actual EIP amount sent to the baseline tax unit, and actual EIP amount associated with the target child), we will produce graphs of the amounts against the running variable (birthday of the target child, re-centered to be days around January 1, 2003). We will also include the amount as a dependent variable plugged into Equation 1 (without covariates) to determine whether tax units/target children with birthdays before January

[20] Individuals not required to file in 2018 or 2019 but who received Social Security retirement, survivor or disability benefits (SSDI), Railroad Retirement benefits, Supplemental Security Income (SSI), or Veterans Affairs benefits got the EIPs automatically.

[21] https://www.irs.gov/pub/irs-pdf/p5420b.pdf.

1, 2003 received less on average than tax units/target children with birthdays after January 1, 2003, and whether this difference is statistically significant at conventional levels.

P2: What evidence supports (or discredits) the idea that families with slightly younger or older children are similar to one another based on observable characteristics?

We will run statistical tests to provide evidence that there is not systematic sorting into treatment and control. First, we will provide graphical evidence by plotting the density of the birthdates around January 1. Second, we will formally test if this density is the same on both sides of the cutoff by running a binomial test.[22] This density test is compatible with our plan to exclude a "donut hole" of children whose birth dates fall proximate to the January 1st threshold (December 24, 2003 - January 8, 2004, where we expect to see manipulation). Instead of testing for manipulation of the running variable at the threshold, we will use a binomial test to evaluate whether there is manipulation of the running variable outside the donut hole window. Finally, we will check for systematic differences in our control and treatment groups by running our main specification (Equation 1, excluding the covariate vector) on predetermined covariates (as described below). Running our specification on predetermined covariates and showing evidence of no treatment effect provides evidence of balance on those covariates.

Causal analysis

Our main analysis seeks to identify the causal impact of eligibility for the EIPs (and the Child Tax Credit of 2019) on our outcomes of interest, listed in the table below. We use the regression specification in Equation 1, above, to capture impacts on these outcomes for the target child.

We plan to measure the causal impacts of eligibility for the EIPs for target children living in low-income, middle-income, and high-income households separately. That is, we plan to run three sets of analyses using Equation 1, where we subset our sample for each of the income groups of interest. For this, we use the tax unit's 2018 adjusted gross income (or its proxy from information returns, as described in the Sample Identification section above). We divide this into three groups: those earning less than $30,000, those earning between $30,000 and $60,000, and those earning above $60,000. We have chosen these cutoffs based on whether the target children from these families are likely to be eligible for Pell grants, which has policy relevance for our primary outcome, college enrollment; however, we plan to run analyses checking if our results are robust to different cutoff levels.

[22] The test is discussed here: Cattaneo, Matias D., Nicolas Idrobo, and Rocío Titiunik. "A Practical Introduction to Regression Discontinuity Designs: Extensions." *Elements in Quantitative and Computational Methods for the Social Sciences*, March 2024. https://doi.org/10.1017/9781009441896.

Outcome variables

Outcome (all for TY 2021)	Definition
Primary outcome	
Child has 1098-T, enrolled at least half-time	1 - Form 1098-T issued by any college or university listing the child's TIN as enrolled at least half-time 0 - otherwise
Child filed a tax return or claimed as a dependent	1 - Child filed tax return as independent tax filer or claimed as a dependent 0 - otherwise (e.g., non-filer)
Secondary education outcomes	
Child has 1098-T from a four-year college, enrolled at least half-time	1 - Form 1098-T issued by a four-year college or university listing the child's TIN as enrolled at least half-time 0 - otherwise
Child has 1098-T from a two-year college, enrolled at least half-time	1 - Form 1098-T issued by a two-year college or university listing the child's TIN as enrolled at least half-time 0 - otherwise
Child filed own tax return	1 - Form 1040 with the child's TIN listed as the primary filer or secondary filer; 0 - otherwise
Child claimed as a dependent	1 - Form 1040 with the child's TIN listed as claimed as a dependent; 0 - otherwise
Child is working	1 - W-2 or 1099-NEC issued by any employer listed the child's TIN and income reported > $0 0 - otherwise
Child is working or in school	1 - Child is enrolled in college (primary outcome) or child is working; 0 - otherwise
Other outcomes and robustness checks	
American Opportunity Tax Credit claimed by the child	1 - American Opportunity Tax Credit claimed by child (or on their behalf when child claimed as a dependent)for an amount > $0

	0 - otherwise (includes non-filers)
Child enrolled in higher education at least half-time	1 - Form 1098-T issued by any college or university listing the child's TIN as enrolled at least half-time or claimed the American Opportunity Tax Credit (AOTC) 0 - otherwise
Child has 1098-T enrolled in higher education, including less than half-time	1 - Form 1098-T issued by any college or university listing the child's TIN in TY 2022 0 - otherwise
Measures of college quality from IPEDS data linked to college EIN where child enrolled at least half-time (using IPEDS data from 2019)	● "college ipeds grad-rates": 150% of regular time completion rates ● "college ipeds grad-rates-pell": 150% of regular time completion rates for Pell recipients To account for the fact that some target children will not enroll in college and have a missing value for these measures of college quality, we plan to derive two categorical measures from each of the two continuous IPEDs graduation rate measures as follows: 1 If a graduation rate is above the median graduation for college of the same type (2-year or 4-year); 0 otherwise (including target children who are not enrolled).

Our primary outcome year is tax year 2021. Tax year 2021 is the year when the majority of children in our sample would have graduated high school and transitioned from high school to college if choosing to enroll. Since academic years typically go from August - May and tax years go from January - December, our analysis of college enrollment using TY 2021 is identifying enrollment during the fall 2021 term. Depending on the findings for TY 2021, we may also explore outcomes in later tax years. However, for lower-income portions of our sample EITC eligibility rules may introduce bias into our analysis for outcomes in TY 2022 and beyond (more on this below).

Covariates

We use the variables in the following table in two potential ways. First, we use them as covariates in our regression models to improve precision. Second, we run Equation 1 (without the covariate vector) with them as dependent variables in order to check for balance around our birth date cutoff to confirm the validity of our identification strategy. The "Use" column in the table below indicates which variables are used as covariates, which are used for validity checks, and which are used for both.

As described above, we chose a baseline year based on the most recent year a target child can be linked to a tax unit, of 2016-2018. However, some information comes from information returns which are available whether a tax unit files taxes in a given year or not. Where relevant, we also indicate in the table whether the variable comes from the tax year in which we are able to link the target child to the tax unit (the link year) or from the primary baseline year, which is tax year 2018.

Measure	Definition	Use
Location		
State in link year	Fixed effects for each of the 50 states and the District of Columbia. Pulled from the address information in the tax unit's Form 1040 in the link year. Includes a dummy equal to one if state is missing, zero else.	Covariate
Link Year		
Target child linked to tax unit in TY 2018	1 if child linked to tax unit using TY 2018 data 0 otherwise	Covariate Validity
Target child linked to tax unit in TY 2017	1 if child linked to tax unit using TY 2017 data 0 otherwise	Covariate Validity
Target child linked to tax unit in TY 2016	1 if child linked to tax unit using TY 2016 data 0 otherwise	Validity[23]
Years claimed as a dependent	Number of years claimed as a dependent in TY 2018, TY 2017, and TY 2016	Covariate Validity
Consistently claimed	1 if child linked to the same tax unit who filed in TYs 2016-2018[24] 0 otherwise, including if child not claimed as a dependent in one or more years	Covariate Validity
Family composition in link year		
Married filing jointly	1 if primary and secondary filer are married and filing jointly	Covariate Validity

[23] Not included as a covariate, since this measure would be collinear with the linking indicators for TY 2019 and TY 2018.
[24] The same tax unit means the child was claimed by the same person or the same two people each of the three years.

	0 otherwise	
Single filer	1 if primary filer files as an independent tax filer 0 otherwise	Validity
Number of dependents	Number of dependents claimed on the tax unit's Form 1040	Covariate Validity
Tax unit finances in baseline year (2018)		
Tax unit has two adult earners	1 if any positive income reported on W-2 or 1099-NEC linked to primary and secondary filer in TY 2018 0 otherwise (including for single filers)	Covariate Validity
Tax unit has one adult earner	1 if any positive income reported on W-2 or 1099-NEC linked to only one of the primary and secondary filers in TY 2018, including single filers with positive income 0 otherwise	Covariate Validity
2018 AGI/AGI proxy	Adjusted gross income from the tax unit's 2018 Form 1040, if available. If tax unit did not file in 2018, total earnings reported in 2018 on W-2 and 1099-NEC for primary and secondary filers linked to target child in link year. 0 if no 1040, W-2, or 1099-NEC for primary or secondary filers in 2018 (Note, this is the variable that is used for EIP eligibility in constructing our sample, as well as for determining after tax income.)	Sample construction Validity Covariate
Has mortgage	1 if Form 1098 Mortgage Interest Statement linked to primary or secondary filer in TY 2018 0 otherwise	Covariate Validity
Social Security retirement or disability (SSDI) income for primary filer	1 if SSA-1099 linked to primary or secondary filer in TY 2018 0 otherwise	Covariate Validity
Has interest income	1 if 1099-INT (interest) linked to primary or secondary filer in TY 2018 0 otherwise	Covariate Validity
Has dividend income	1 if 1099-DIV linked to primary or secondary filer in TY	Covariate

	2018 0 otherwise	Validity
Has Unemployment Compensation income	1 if 1099-G with a positive value in Box 1 is linked to the primary or secondary filer in TY 2018 0 otherwise	Covariate Validity
Tax unit Child Tax Credit Benefit amount in baseline year child linked to tax unit		
Refundable child tax credit amount claimed by tax unit in baseline year	Amount of refundable child tax credit benefit for the tax unit; $0 if Child Tax Credit is not claimed.	Covariate Validity
Non-Refundable child tax credit amount claimed by tax unit in baseline year	Amount of refundable child tax credit benefit for the tax unit; $0 if Child Tax Credit is not claimed.	Covariate Validity
Information returns for target child		
Employment	1 if any positive income reported on W-2 or 1099-NEC linked to target child in TY 2018 0 otherwise	Covariate Validity
Enrolled in college	1 if Form 1098-T linked to child in 2018 0 otherwise	Covariate Validity
Female	1 if female on birth certificate 0 otherwise[25]	Covariate Validity

Subgroup analyses

We are interested in learning about the heterogeneity in treatment effects for different sub-populations, specifically among members of socially disadvantaged communities or groups that have experienced systemic discrimination. Our subgroups are defined in two ways: individual-level characteristics, and location-based measures.

Our first individual-level measure is income. We divide 2018 AGI (or its proxy) into three categories, as described above in our main causal analysis section. We plan to look at impacts on all of our outcome variables subsetted to these groups; that is, for each outcome variable, including primary, secondary, and other outcomes, we will run three regressions, one for each income subgroup. For our other subgroup analyses, we will only look at impacts on our two primary outcomes of interest

[25] We will include an indicator for missing, if no data are available.

Our second individual-level measure is race and ethnicity. We do not observe race or ethnicity in our data; however, the IRS has developed race imputations using Bayesian Improved First Name and Surname Geocoding (BIFSG). This generates a probability that an individual belongs to a certain racial/ethnic group. We will assign an individual to a given group if their probability of belonging to that group is greater than 75%.[26] Race imputations are available for the primary filer on a tax return only, so we do not know the imputed race of the target child. We use the imputed race of the primary filer associated with the target child in our link year to proxy for the race of the target child. The race/ethnicity combinations we are able to identify are non-Hispanic white, non-Hispanic Black, non-Hispanic Asian, and Hispanic.

To construct our location-based measures, we will rely on the address information for the target child in the link year (the most recent year, of 2016-2018, in which the child is claimed as a dependent and thus can be linked to a tax unit).

Our first location-based measure is the Social Vulnerability Index from the CDC. The SVI uses American Community Survey five-year estimates to generate 15 measures of vulnerability (based on poverty status, race, and disability, among others).[27] It ranks Census Tracts on the proportion of people in the tract who are vulnerable according to these measures, creating a final percentile ranking of all Census Tracts in the US compared to one another. We will use their rankings as of 2020 to identify individuals who live in high vulnerability, medium vulnerability, and low vulnerability Census Tracts, as defined by the tract scoring in the top, middle, and lowest third, out of all tracts in the country. Since our data on target children gives us the ZIP code and not the Census Tract, and Census Tracts and ZIP codes do not have a 1:1 correspondence, we will assign the child to a census tract using the Census 2020 ZIP code tabulation area (ZCTA) to Census Tract relationship file.[28]

Our second location-based measure comes from Opportunity Insights data, based on work by Chetty et al. (2022).[29] They look at measures of social connectedness among people in different ZIP codes, and correlate this with rates of economic mobility. Following this, we define a target child as living in a high, medium, or low socially connected ZIP code based on the quintile of connectedness in the OI data.

To understand the impacts of eligibility for the EIPs among these different subgroups, we run Equation 1, but restricted to the relevant subsample. For the individual-level race and ethnicity subgroups, as well as the two location-based subgroups, we additionally restrict our analysis to those people who are also low or middle income, as defined below. For example, for our analysis of

---

[26] Elzayn et al. (2023) estimate the rates of false positives and negatives, looking only at estimated probabilities of Black and non-Black. A 75% threshold produces a false positive rate of 3.4% and a false negative rate of 53%. In robustness checks, we may also look at additional threshold values for our race definitions. Elzayn, Hadi, Evelyn Smith, Thomas Hertz, Arun Ramesh, Robin Fisher, Daniel E. Ho, and Jacob Goldin. "Measuring and Mitigating Racial Disparities in Tax Audits," January 30, 2023. https://github.com/jacobgoldin/jg_website/blob/35c7e44419b0c3473041229c1f82b5a96e66b04d/audit%20disparities%201-30-23.pdf.

[27] https://www.atsdr.cdc.gov/placeandhealth/svi/index.html

[28] https://www.census.gov/geographies/reference-files/time-series/geo/relationship-files.2020.html#zcta

[29] Chetty, Raj, Matthew O. Jackson, Theresa Kuchler, Johannes Stroebel, Nathaniel Hendren, Robert B. Fluegge, Sara Gong, et al. "Social Capital I: Measurement and Associations with Economic Mobility." *Nature* 608, no. 7921 (August 2022): 108–21. https://doi.org/10.1038/s41586-022-04996-4.

effects for individuals living in high social vulnerability census tracts, we would restrict to people who are in those tracts and are themselves low or middle income. This is because we expect the EIPs to have the greatest impacts on decision-making for low and middle income families due to the size of the payments relative to income. We do not plan to further limit the sample to low-income separately from middle-income groups to preserve statistical power. We report, as before, on β_1. We do not expect to run statistical tests comparing β_1's across subgroups. As stated, above, we plan to conduct the subgroup analyses of effects only on our two primary outcome variables (with the exception of the income subgroups, for which we will plan to analyze the effects for each subgroup for all outcome variables).

Measure	Categories	Definition
	Main analysis	
Individual level: looking at effects on all outcome variables		
Tax unit adjusted gross income during the baseline year (TY 2018), or its proxy	Low	$30,000 or less
	Middle	$30,001 - $60,000
	High	Greater than $60,000
	Additional subgroup analysis	
Individual level: effects only on primary outcome variables		
Race/ethnicity	White	Proxy for target child identified as non-Hispanic white
	Black	Proxy for target child identified as non-Hispanic Black
	Asian	Proxy for target child identified as non-Hispanic Asian
	Hispanic	Proxy for target child identified as Hispanic
Location-based measures: effects only on primary outcome variables		
CDC Social Vulnerability Index of 2020	High vulnerability	Census tract scores in the 66th percentile or above on the summary vulnerability indicator
	Medium vulnerability	Census tract scores between the 33rd and 65th percentiles on the summary vulnerability indicator
	Low vulnerability	Census tract scores below the 33rd percentile on the summary vulnerability indicator
Social capital measure of economic	Low	Bottom quintile in economic connectedness (ec_zip) in friendships between low-SES and high-SES individuals living in a given zip code

connectedness[30]	Medium	Middle three quintiles in economic connectedness (ec_zip) in friendships between low-SES and high-SES individuals living in a given zip code
	High	Highest quintile in economic connectedness (ec_zip) in friendships between low-SES and high-SES individuals living in a given zip code

Limitations and exploratory analyses

Earned Income Tax Credit and Child Tax Credit in infancy

Many researchers have documented the long-term benefits of early investments on lifetime earnings and academic success. Most relevant to the current evaluation comes from Barr et al. (2022) who documented effects of being eligible for additional tax benefits in the first year of life on these longer-term outcomes.[31] The majority of tax benefits for claiming young children as dependents come from the Earned Income Tax Credit (EITC) that is available to low-income earners only and the Child Tax Credit (CTC) that is available to low-income earners as well as moderate- and high-income earners. This is an important potential threat to the validity of our analysis, because the timing of when families receive these first tax benefits depends on the same birth date cutoff (January 1, 2003) used to determine eligibility for the EIPs: families of children born before the end of the tax year can receive benefits when the child is roughly 2-4 months of age, versus at 13-15 months of age for children born just after the end of the tax year (since they have to wait until the following spring to claim the child for the tax year in which the child was born). If payments in the first year of life (as opposed to the second year) have positive impacts on our outcome variables, we could underestimate the impacts of the EIPs, as the younger children in our sample could have received the EIPs, while the older children could have received the CTC and EITC in the first year of life.

We account for these early payments by running exploratory analysis where we split our sample into tax units who we predict to be eligible for EITC those who predict were not. We plan to use the follow procedure to predict eligibility:

1. Identify the primary and if applicable secondary filer linked to the target child during the early childhood period.
2. Predict their eligibility for EITC in TY 2002 (claimed in spring 2003) using the following information:

[30] More information about this data source, including links to the data codebook, and academic papers, including Chetty et al., (2022) can be found on the Opportunity Insights webpage: "Social Capital I: Measurement and Associations with Economic Mobility."

[31] Barr, A., Eggleston, J., & Smith, A. A. (2022). Investing in infants: The lasting effects of cash transfers to new families. *The Quarterly Journal of Economics*, *137*(4), 2539-2583.

a. Family structure based on information from 1040 filed in the year the target child was linked to a tax unit during the early childhood period. Note that we'll adjust the ages for children claimed as dependents to their ages as of the end of 2002, with the exception that we'll assume all families have at least one child (i.e., the target child) for EITC and CTC eligibility purposes.

b. Information returns from the primary (and if applicable) secondary filers in TY 2001.

We run analysis for each of these groups separately to answer slightly different research questions described below:

- While eligibility for EITC in TY 2002 is a limitation of our analysis for isolating the effects of the EIPs, it also becomes a feature of our data when we consider a different research question on when during the life course do investments matter most. By limiting the sample to those eligible for EITC during infancy, we will be able to generate suggestive evidence on the differences in effects between the investments in the first months of life compared to the effects of liquidity when making college choice decisions on low-income children's college enrollment decisions.
- By limiting our sample to tax units who are too high income to be eligible for EITC, the slightly older children do not get additional benefits from EITC than the slightly younger children during infancy. This allows us to better isolate the effects of eligibility for the EIPs from the effects of eligibility for EITC during childhood. However, given the higher-income threshold for the Child Tax Credit of 2002, we do not limit our sample further based on income eligibility and instead acknowledge that eligibility for these benefits in infancy could be a source of bias in our results, even among this higher income group.

If we are able to obtain additional data, we also plan to include placebo years in our analysis to help disentangle the effects of the eligibility for different benefits and the timing of when children and their families would receive these benefits. To do so, we would use data from two placebo years, in which children are born in years that are ***not*** used for age-based eligibility cut offs for EIPs or the Child Tax Credit of 2020 and 2021. These years are:

- Placebo cohort 1: born around the threshold of January 1 2002 - High school class of 2020
- Placebo cohort 2: born around the threshold of January 1 2005 - High school class of 2023

In these placebo years, children born in December and January are both eligible to be claimed as dependents for the purposes of EITC and the Child Tax Credit for the same number of years; however, the timing of when these benefits are made differ. The children born in December are first eligible to receive tax benefits a few months after they are born whereas children born in January must wait until the following tax year. In contrast, children born in December are eligible for their last year of benefits approximately a year before children born in January.[32] In placebo

[32] In most tax years, children must be under age 19 (under age 17) at the end of tax year to be claimed for the purposes of EITC (CTC).

cohort 1, the children were too old to be eligible to be claimed as dependents for EIPs or the Child Tax Credit of 2021. In placebo cohort 2, the children were eligible to be claimed as dependents for EIPs and the Child Tax Credit of 2021, but would have received these benefits before the sensitive period when they were making college choice decisions.

The focal cohorts are the same as the placebo cohorts in that the timing of their first and last year of benefits as a dependent depends on whether the child is born in December or January. The focal cohorts differ from these placebo cohorts in that none of the members of these placebo cohorts are eligible for additional tax benefits when they are making college choice decisions. Including these additional cohorts in our analysis, should help us disentangle the effects of payment timing from the effects of eligibility for additional benefits.

Complier effects

The main analysis is an ITT specification focused on children who are likely eligible for EIP payments.. If feasible, we plan to conduct an exploratory analysis that examines the impact among compliers, or target children in the sample who, in addition to being eligible for the EIP payments, received them. To do so, we will use the second strategy for identifying EIP amounts described in section P1, above, which focuses on finding the target child first, and then linking that child back to a tax unit to determine the actual amount of EIPs associated with that target child.

We will then repeat the specification for Research Questions 2-5 but use the two-staged least squared approach to analyzing compliance—so fit a first stage regression predicting receipt of the benefit using the same covariates as in the main analysis and then using the fitted values (and appropriate standard error correction) to analyze the impact on compliers.

Child Tax Credit of 2019, Other Dependents Tax Credit, and state-level Child Tax Credit

While the slightly older children are not age eligible for the EIPs, they are eligible to be claimed as a dependent for the purposes of the Other Dependents Tax Credit in TY 2019 (i.e., concurrently with the timing of the first EIP). Eligibility for the benefit may offset some of the effect of eligibility for the EIPs.

Additionally, the slightly younger children (who would not have been eligible for the CTC in their first year of life) are eligible to be claimed for the federal Child Tax Credit when they are 16 (again, concurrent with the EIPs), while the slightly older children are not. Certain states also have state-level CTCs which use the same age cutoff (Arizona, Idaho, Maine, New York, and Oklahoma).[33] Thus we cannot attribute any impacts on our outcome variables entirely to the EIPs. However, we plan to account for this limitation by presenting information on the actual difference in benefit receipt (the EIPs plus any other tax benefits) and after-tax income.

[33] https://www.ncsl.org/human-services/child-tax-credit-overview.

1098-T Form coverage

In some cases, schools and universities may not provide the 1098-T Form to enrolled students. This happens when the students pay for college entirely through grants. Since in these cases the student does not owe tuition and fees, colleges are not required to report the Form 1098-T to the student or the IRS and only some choose to do so. This most often occurs among two-year community colleges where Pell Grants are more likely to cover the full cost of tuition and fees. This occurs both because tuition and fees are low and students at these schools, who are often low income, are more likely to qualify for Pell Grants.

This missing data problem could introduce bias if eligibility for the tax benefits changes the types of college in which students apply and enroll. For example, consider a child who would enroll in a two-year community college without the additional income, but would enroll in a four-year college with the additional income. In this case, they would only be linked to a 1098-T Form when enrolled at the four-year college. That is we would underestimate enrollment in two-year colleges and be more likely to do so when the target child was not eligible for additional funds. In this scenario, we would differentially observe outcomes on college enrollment for those who are eligible for benefits compared to those ineligible for tax benefits.

We plan to account for this limitation by:

- Including take-up of higher education tax credits as part of our measure for college enrollment, since families can take up these benefits even if they do not have a Form 1098-T;
- Examine the effects on enrollment in four-year college, where grants are less likely to cover the full cost of college;
- Examine the effects among children from middle- and high-income families who are less likely to have the full cost of tuition covered by grants; and
- (if feasible) run robustness checks where we limit our sample to students living in states where colleges appear to report Form 1098-T data for all students, even for students who owe no tuition and fees.

TY 2022 and beyond

Qualifying child eligibility rules for the purposes of the Earned Income Tax Credit include that the child needs to be under age 19 at the end of the tax year or under age 24 at the end of the tax year and a full-time student for at least five months of the year. While all of the children in our sample meet the requirement of under age 19 in TY 2021, when we measure our outcomes, they would not meet this requirement in TY 2022 and later. Thus, for the full sample, examining the effects of eligibility for the EIPs on continued enrollment after TY 2022 could be picking up the effects of changes in eligibility for EITC. One approach that could circumvent this issue is to limit the sample to tax units unlikely to be eligible for EITC (i.e., middle and higher income families) or limit the sample to families where three or more other children in the household are younger than the target child. We also will plan to model the amount of the EITC the family is eligible.

Robustness checks

As described above, we plan to run the following analyses to check our results for robustness to different specifications.

Sample specification

States with kindergarten cutoffs determined by LEA

As described above, we exclude from our analysis children who, at the time they were of the age to start kindergarten, were living in a state where the cutoff date by which the child had to turn 5 in order to start school fell on or near the cutoff we use for our regression discontinuity, January 1. An additional five states leave the kindergarten start date cutoff up to the Local Education Authority (LEA, aka school district): Colorado, New Hampshire, New Jersey, New York, and Pennsylvania). We include children living in these states in our main specification, but drop them in a robustness check.

We will also run a version where we include children living in California and Michigan as of age 5, since these states have a kindergarten start date cutoff that falls within our 31 day window (California's is Dec. 2, Michigan's is Dec. 1) but not at January 1.

Full sample

Our main sample uses a number of indicators that allow us to identify children more likely to be eligible for EIPs (and thus more likely to show impacts), as well as exclude children for whom our regression discontinuity design is likely to be invalid. These indicators primarily come from returns filed by the parents/guardians of the children in our sample. However, this means that children of non-filers are excluded from the specifications. Since low income families are less likely to file, this choice of sample has implications for the external validity of our results. Thus we plan to run a version of our regressions that places no sample restrictions on the target children beyond having a birthday that falls within the 31 day window from January 1. This specification will not include covariates (since covariates cannot be observed for all children). We will also run a second specification using this same sample, but imputing values for covariates. We will compare the results of these to results from our main sample.

Income cutoffs

Our main specifications look at impacts separately in income subgroups, defined by AGI less than $30,000, between $30,000 and $60,000, and over $60,000. In robustness checks, we will look at whether our results change when we adjust these thresholds. We will also run a version of Equation 1 in which we employ the full sample, but interact the binary indicator for treatment ($1[z_i>0]$) with AGI, to see how treatment effects respond to an increase in income.

State Child Tax Credit eligibility

While our measure for eligibility for tax benefits should take into account state implemented tax benefit programs that use the same cut off, we plan to do a robustness check that drops children living in states during the baseline period that use the same cutoff for eligibility for state implemented Child Tax Credit programs. This includes children living in Arizona, Idaho, Maine, New York, and Oklahoma.[34]

Regression specification

Window specification

Our regression discontinuity model relies on the assumption that, within a window around the cutoff in the running variable (in this case, the number of days between the child's birth date and January 1), assignment to "treatment" (in this case, eligibility for the EIPs) is as good as random. This requires selection of an appropriate window. For our main specification, as described above, we propose to follow Barr et al. (2022) and exclude children from the sample whose birth dates fall more than 31 days from January 1. However, as a robustness check, we will also implement the data-driven window selection approach presented in Cattaneo et al. (2024),[35] and implemented using the rdwinselect package available in both R and Stata. We will allow the software to pick a window no more than 45 days from January 1, to avoid concerns about including children who would have started kindergarten a year earlier due to their state's kindergarten start date cutoff falling in late October. We will run our primary analyses in the alternate window selected by the software.

Donut size

The "as good as random" assumption also implies that members of the treated and control groups either don't know about the cutoff in the running variable, or that there is no action they can take that would move them above or below this cutoff. If this does not hold, then there may be selection into treatment, violating the assumption of independence between treatment assignment and potential outcomes. As described above, to avoid potential manipulation of children's birthdays around the holiday season, following Barr et al. (2022), we exclude from our sample children born within 8 days of January 1 (i.e., we run a "donut" RD). We will also check if our main specification is robust to changing this donut to 5 or 10 days.

Inference

We intend to use large sample methods for inference. That is, we run OLS regressions in the relevant window, using robust standard errors clustered by tax unit. However, we will also run our regressions using the rdlocrand package provided by Cattaneo et al. (2024), which employs Fisherian inference, to determine if our conclusions hold using this alternate inference procedure.

Regression discontinuity assumption

[34] https://www.ncsl.org/human-services/child-tax-credit-overview.

[35] Cattaneo, Matias D., Nicolas Idrobo, and Rocío Titiunik. "A Practical Introduction to Regression Discontinuity Designs: Extensions." *Elements in Quantitative and Computational Methods for the Social Sciences*, March 2024. https://doi.org/10.1017/9781009441896.

We plan to rely on local randomization for the validity of our regression discontinuity design; that is, conditional on falling in the window around the discontinuity, assignment to treatment is as good as random. However, if our tests of balance on covariates show evidence of correlation between covariates and our running variable, then we may fall back on the slightly less strict assumptions required for implementing a continuity-based RD.

<u>Thresholds for coding race/ethnicity (for subgroup analysis)</u>

We will vary the threshold we use to convert the predicted probabilities of membership in a particular racial/ethnic group to the binary indicator of group membership. While the main analysis uses a 0.75 threshold, we will examine the sensitivity of the subgroup analysis to thresholds of 0.6 and 0.9.