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ADMINISTRATIVE BURDENS AND CHILD MEDICAID AND CHIP ENROLLMENTS

Iris Arbogast
Anna Chorniy
Janet Currie

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ABSTRACT

Following decades of increasing child access to public health insurance, pre-pandemic enrollments fell in many states after 2016 and the number of uninsured children increased. This study provides the first national, quantitative assessment of the role of administrative burdens in driving this drop in child health insurance coverage. In addition, we identify the demographic groups of children who were most affected. We show that regulations that increased administrative burdens placed on families reduced public health insurance coverage by a mean of 5.9% within six months following the implementation of these changes. Declines were largest for Hispanic children, children with non-citizen parents, and children whose parents reported that they did not speak English well. These reductions were separate from and in addition to enrollment declines among Hispanic children following the announcement of a new public charge rule in Sept. 2018.

Iris Arbogast
Federal Reserve Bank of St. Louis
irisarbogast@gmail.com

Anna Chorniy
Northwestern University
420 E. Superior St. 9-941
Chicago, IL 60611
anna.chorniy@northwestern.edu

Janet Currie
Department of Economics
Center for Health and Wellbeing
185A Julis Romo Rabinowitz Building
Princeton University
Princeton, NJ 08544
and NBER
jcurrie@princeton.edu

Administrative burdens, defined as the "learning, psychological, and compliance costs that citizens experience in their interactions with government" (Moynihan, Herd, and Harvey 2015, 43), can have a significant effect on the take-up of social benefits (Nichols and Zeckhauser, 1982; Currie, 2006; Sommers et al. 2012). Administrative burdens are sometimes conceived of as a way to target benefits more effectively (Nichols and Zeckhauser, 1982) and/or reduce moral hazard (Brot-Goldberg et al. 2023). However, there is growing evidence that administrative burdens can screen out the neediest potential recipients, exacerbating social inequalities (Bertrand, Mullainathan and Shafir, 2004; Cherlin et al, 2002; Christensen et al., 2020; Currie, 2006; Currie and Gavhari, 2008; Currie et al., 2001; Deshpande and Li, 2019; Finkelstein and Notowidigdo, 2019; Herd and Moynihan, 2018).

After initially increasing following the Affordable Care Act in 2014, the number of insured children in the U.S. started falling after 2016. The number of children without health insurance rose from 4.7% in 2016 to 5.7% in 2019, while among Hispanic children, this number rose to 9.2% by 2019 (Alker and Corcoran, 2020). These losses were entirely accounted for by declines in public insurance since private health insurance coverage remained constant. The downswings in enrollment occurred in the absence of significant changes in eligibility for public health insurance or increases in CHIP premiums because states were forbidden from lowering income eligibility cutoffs or raising CHIP premiums by the "maintenance of effort" provisions included in the Affordable Care Act (Miskel and Alker, 2017) and in coronavirus relief legislation (Dolan et al., 2020).

This study provides the first national, quantitative assessment of the role of several types of administrative burdens in driving the pre-pandemic drop in child health insurance coverage. In addition, we undertake to identify the groups of children who were most affected. Health insurance coverage in childhood has been shown to have significant benefits for children's short- and long-term health, educational attainment, labor supply, and earnings (Brown et al., 2020; Cohodes et al., 2016; Currie and Gruber, 1996; Miller and Wherry, 2019). Indeed, Hendren and Sprung-Kayser (2020) estimate that over the past 50 years, each $1.00 spent initially expanding public health insurance for children paid the government back $1.78 in future benefits. Hence, the downturns in child Medicaid and CHIP enrollments that occurred in many states between 2016 and 2019 are disturbing and bear further investigation (Currie and Chorniy, 2021).

Moreover, though pandemic era freezes on redeterminations of eligibility and the pandemic-induced recession caused child Medicaid and CHIP enrollments to climb during the COVID-19 public health emergency, reports suggest that as many as 7.2 million children will lose health insurance coverage now that the measures put in place during the public health emergency have ended, even though many of them will remain eligible for coverage (Tolbert and Ammula, 2023). The negative pre-pandemic trends in many states suggest that decades of progress increasing children's health insurance coverage are in danger of being at least partially reversed.

Previous case studies suggest that administrative barriers can prevent children from enrolling in Medicaid and CHIP (Heinrich et al., 2022; Moynihan, Herd and Rigby, 2016, Wu and Meyer, 2023), so it is possible that these barriers played a role in the national pre-pandemic reduction in public health insurance coverage for children from 2016 to 2019. To investigate this relationship, we assembled a new dataset of state policies that have affected such burdens. Some of the changes we focus on were in response to measures the federal government took to enhance Medicaid and CHIP program "integrity," including expanded audits of state beneficiary eligibility determinations, and requirements to submit "enhanced" data to the federal government.[1] This study seeks to provide a sense of the extent to which these burdens contributed to the declines in child Medicaid and CHIP enrollments and to identify the most affected populations.

Estimates using monthly administrative data on Medicaid plus CHIP caseloads show that conditional on other policy changes that affected enrollments, increases in administrative burden, were responsible for an initial overall enrollment decline of 1.7 percentage points (4.0%) when first adopted. The magnitude of these impacts tended to grow over time reaching a peak decline of 2.5 percentage points (5.9%) by six months after the policy change. An event study analysis suggests that these negative effects persisted for at least two years after the policy changes. Investigating the same issues using inference procedures designed to account for variation in treatment timing from Callaway and Sant'Anna (2021) yields even larger aggregate impacts of a 3.1 percentage point overall decline in enrollments, which persists and rises to 3.5 percentage points after 20 months.

The second part of the analysis turns to self-reported data from the American Community Survey (ACS) to ask who is most affected by these burdens? We show that changes in overall reported combined Medicaid and CHIP enrollments are more than three and a half times as large for Hispanic compared to non-Hispanic children, and four times greater for children whose parents report that they do not speak English well compared to other children. We also find effects that are roughly three and a half times larger for children with a non-citizen parent than for those with citizen parents, suggesting that immigration-related concerns may have magnified the impacts of administrative burdens.

[1] See for example: https://www.cms.gov/newsroom/press-releases/cms-announces-initiatives-strengthen-medicaid-program-integrity.

For Hispanic children, we show that declines in enrollment from administrative burdens were in addition to declines in enrollment stemming from the announcement of a new public charge rule in Sept. 2018. According to the new rule, someone who was deemed a public charge could be denied entry into the United States or have an application for a legal permanent residency turned down. Previously, people could use public health insurance programs without being considered a public charge. The new rule changed that by making having health care needs, lack of private health insurance coverage, or previous use of public programs negative factors in determinations about being a public charge by immigration authorities (KFF, 2019). Even though the law was later reversed, it may still be having a chilling effect on enrollments in public health insurance.

The rest of the paper proceeds as follows: Section 1 provides a discussion of the data on Medicaid and CHIP child enrollments, as well as the new measures of administrative burden and other relevant policies that we have collected. Section 2 gives an overview of our methods, section 3 shows the results, and section 4 presents a discussion and conclusions.

I. Data and Characterization of Administrative Burden

Medicaid and CHIP are the two largest U.S. public health insurance programs for children. Both are means tested and CHIP covers children at somewhat higher income levels than Medicaid. Many states use money from the federal CHIP program to expand their Medicaid program, that is, they do not run a separate CHIP program. This is the main reason that we analyze Medicaid and CHIP enrollments together.

The analysis is based on three main sources of data: state Medicaid and CHIP child enrollment counts from the Center for Medicare and Medicaid services (CMS), the annual

American Community Survey (ACS), and a database of changes in state regulatory policies including data on new regulations that impacted administrative burden.

A. ADMINISTRATIVE MEDICAID AND CHIP ENROLLMENT DATA

Administrative Medicaid and CHIP enrollment data comes from the federally run Medicaid.gov database which includes Medicaid and CHIP enrollments collected from states by CMS.[2] In the analysis of the monthly state-level combined Medicaid and CHIP data from CMS, the time period is 2014 to 2020. Due to changes in the way the data was collected and reported following the implementation of the Affordable Care Act, comparable data on Medicaid enrollments is not available prior to 2014. The main variable used, combined Medicaid and CHIP child enrollment, represents the total number of children enrolled in Medicaid and in any separate CHIP programs as of the last day of each month.[3] Data for North Carolina, Tennessee and Arizona come from state-provided databases.[4] The combined Medicaid and CHIP enrollment numbers are converted to rates by dividing by the total population of children ages 0

[2] We found and corrected for the following data quality issues. Several observations that appeared to be reporting outliers were dropped and then interpolated for North Dakota (6/2016 and 7/2016), Illinois (3/2015), Nevada (6/2019, 11/2019, and 7/2020), Iowa (5/2014), and Michigan (5/2015). Of these, only Illinois is a treatment state as shown in Table 1. We treat as missing time periods 10/2016 to 5/2017 in Ohio and 6/2017 to 12/2017 in New Mexico. Months are flagged as outliers if changes in enrollment were sharp and returned to the previous point immediately after the departure from the trend. Some states' data is unavailable in the beginning of the dataset. Data starts in 9/2014 in Arkansas, 2/2017 in California, 5/2014 in Connecticut, 2/2014 in Georgia, 4/2014 in Illinois, 4/2014 in Iowa, 4/2014 in Kansas, 6/2014 in Nevada, 6/2016 in New Mexico, 7/2014 in North Dakota, 5/2014 in Rhode Island, and 9/2014 in Wisconsin. The District of Columbia was dropped because it showed unrealistic volatility in monthly enrollments.

[3] See https://www.medicaid.gov/medicaid/national-medicaid-chip-program-information/medicaid-chip-enrollment-data/methodology-about-medicaid-chip-enrollment-report/index.html for further information about these data.

[4] Data for North Carolina is from the "Medicaid and Health Choice Enrollment Reports," available at: https://medicaid.ncdhhs.gov/medicaid-and-health-choice-enrollment-reports. The North Carolina Medicaid.gov data had a large discontinuous drop in 2017 that was not present in the state-provided data. Data for Arizona was missing from Medicaid.gov so we use data from the Arizona Health Care Cost Containment System Document Archive Population Demographics documents available here: https://archive.azahcccs.gov. It is available for children ages 0 to 17 (i.e. not 18) on a quarterly basis, which we treat as monthly in our analysis. Data for Tennessee was only present on Medicaid.gov from 2019. We use data from the Division of TennCare, available here: https://www.tn.gov/tenncare/information-statistics/enrollment-data.html.

to 18 in that state and year from the American Community Survey, created using the standard ACS-provided weights.

We also use an unduplicated count of the number of children enrolled in Medicaid plus CHIP during the federal fiscal year to measure enrollment churn. We create the churn measure by subtracting the number of children enrolled in Medicaid plus CHIP at the end of the federal fiscal year (September) from the annual unduplicated count of all the children who were enrolled at some point in the year and then dividing by the annual unduplicated count.[5] Hence, this number provides an indicator of the number of children who were enrolled at some point during the year but exited before the end of the fiscal year. A child who was enrolled in more than one program is only counted once. This annual data is sourced from the federally run Statistical Enrollment Data System.[6]

B. DATA ON ADMINISTRATIVE BURDEN AND OTHER POLICY CHANGES

There are many different types of administrative policies that might affect combined Medicaid and CHIP enrollments. For example, Sommers et al. (2012) focus on an earlier time period and look at factors such as the availability of a combined family application, joint applications for programs (e.g. Medicaid and SNAP), interview requirements, the frequency of redetermination intervals, and the availability of applications in languages other than English. We take advantage of what has become the standard reference in this literature, the work of the Kaiser Family Foundation, KFF (2022a) and Brooks et al. (2021). KFF has been tracking Medicaid and CHIP administrative policies since 2000 by surveying state program officials, reviewing state plans,

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[5] We drop negative values for churn.

[6] See https://www.medicaid.gov/chip/reports-evaluations/index.html#:~:text=Each%20year%2C%20CMS%20collects%20data for further information.

and interviewing state child health advocates. We use their database to measure many policies that affect enrollment, including income cutoffs, premiums, ACA Medicaid expansions status, work requirements, and redetermination pauses.

However, two authors of the annual KFF report wrote a separate article (Artiga and Pham, 2019) pointing out that in many states, new increases in administrative burdens that were not being tracked by KFF were also having an important impact on enrollments. In order to identify other policies that could affect enrollment during our sample period, we conducted Google searches with the following string of search terms: "Medicaid", "CHIP", "enrollment drop", "child", and "eligibility," entered in conjunction with each specific state and year. For example, including the first five terms, plus "Missouri," and "2017" locates several references to Missouri's 2017 law change. This law change implemented an automated eligibility checking process beginning in 2018 and was thought to have substantially reduced enrollments. By searching in the same way for every state-year combination, we were able to find references to policies that were thought to have affected administrative burdens over our time interval. More information about the specific policy changes appears in Appendix Table 1.

These new administrative procedures can be divided into two major categories: increases in the stringency and frequency of eligibility and income checks, and what might be termed "automatic disenrollment." This latter provision might take the form of cancelling someone's coverage without notice after mailing out a paper renewal packet if the person has not responded within 10 days. In most cases, families were not aware that they had lost coverage until they tried to seek care. We show below that the estimated effects of these two types of policies are statistically similar, which is why in most of our analyses we considered them as a combined "administrative burden" variable.

For each state, columns 1, 2, 5 and 6 of Table 1 lists the dates that these new additional measures of "administrative burden" were implemented. Further details about these individual state policies appear in Appendix Table 1. Over the sample period, fifteen states adopted either more stringent or frequent income or eligibility checks or automatic disenrollment.

<Table 1 about here>

For example, in October 2014 Texas Medicaid increased the frequency of income eligibility verification. Texas now checks income for households with children on Medicaid in the 5th, 6th, 7th, and 8th months of their enrollment period each year. If the family's income appears to increase over the eligibility limit, they have 10 days to prove that this is an error, or they lose coverage. If multiple children in the family are enrolled in Medicaid at different times, the eligibility checks could be on different timelines creating even more burden (Luthra 2017; Texas Health and Human Services, 2015).

As a second example, in April 2017, Mississippi enacted the Medicaid and Human Services Transparency and Fraud Prevention Act which requires a private contractor (such as Equifax, which lobbied for the law) to check the eligibility of Medicaid enrollees (Fifield, 2017; Medicaid and Human Services Transparency and Fraud Prevention Act). Another important change was to switch from requiring reporting of income changes that cause income to exceed 130% of poverty (Mississippi Department of Human Services, 2017) to requiring recipients to report all changes in income of more than $100 (adjusted for inflation after fiscal year 2018), as well as any changes in the source of income, address, household composition, liquid resources, and child support -- all within 10 days of the change (7 CFR, 1978).

A third example is that in 2017, Missouri passed legislation to implement an automated eligibility checking process for Medicaid enrollees (Mo Rev Stat, 2018). Enrollees who could not be verified through cross-checking federal or state data were sent a letter via U.S. mail and had 10 days to respond or they were automatically disenrolled. Nearly 80 percent of those who lost coverage were children (Fentem, 2019). According to a survey of 37 health care providers collectively serving nearly every region of the state, 87 percent of patients who lost Medicaid coverage still met income eligibility requirements but lost coverage due to challenges with the renewal process. Eighty-four percent of these patients were unaware that they had lost coverage until attending or scheduling an appointment (Kids Win Missouri, Missouri Budget Project and Missouri Coalition of Children's Agencies, 2019).

In most cases, states adopted only one of these "burden" policies suggesting that they were viewed as substitutes. The exceptions are Illinois and Louisiana. Both adopted both an increase in the frequency or stringency of eligibility checking and automatic disenrollment. In Louisiana, these two policies were both implemented at about the same time. In Illinois, the frequency policy was adopted in 2013 while the automatic disenrollment policy was adopted in 2018.

In many states with increases in administrative burden, it appears that enrollees were terminated for reasons other than ineligibility. In other words, it is not the case that these increased administrative requirements acted mainly by weeding out ineligible enrollees. For example, in Arkansas in June 2018, only 11 percent of terminations were due to household's increased income while 60 percent were due to enrollees not returning paperwork or the state being unable to locate the enrollee, often due to incorrect addresses in the system (Hardy, 2018).

Turning to other types of policy changes documented by KFF, columns 3, 4, 7 and 8 of Table 1 focus on two types of policy changes stemming from the 2010 Affordable Care Act that tended to increase child Medicaid and CHIP enrollments: Medicaid expansions and redetermination pauses. Many states expanded their Medicaid programs when the option to do so became available on January 1, 2014, while other states adopted the expansion later or chose not to adopt so that the timing of adoption varied widely, as illustrated in the table.[7] Prior to 2021, 36 states had expanded their Medicaid programs. These expansions covered previously ineligible low-income adults and so did not apply directly to children. Nevertheless, although most low-income children were already eligible for Medicaid prior to the ACA expansions, states that expanded access to adults also saw increases in child enrollments (Hudson and Moriya, 2017). We control for whether the state had adopted the ACA Medicaid expansions as of the month of enrollment in all our models.

Pauses in redeterminations represent a second set of policy changes that tended to increase Medicaid enrollments. They mechanically increase caseloads by preventing children from being removed from the rolls. Table 1 shows that when states transitioned to the ACA in 2014, 35 states obtained waivers from the federal government which allowed them to pause redeterminations for Medicaid and/or CHIP so that they could transition to new ACA-compliant processes for handling renewals. The federal Coronavirus Aid, Relief, and Economic Security Act or CARES Act, signed into law on March 27th, 2020, also suspended Medicaid redeterminations nationwide for the duration of the health emergency caused by COVID-19. This suspension led to sharp upswings in Medicaid and CHIP enrollments since people stopped leaving the rolls. In what follows we capture the effect of these pauses with an indicator that is equal to one if a redetermination pause was in effect and zero otherwise.

Work requirements have received a great deal of attention but have so far been implemented only in Arkansas. We have included them in the analysis because they are an

[7] Data on the timing of adoption comes from KFF (2022b).

important focus of national conversation. Arkansas implemented a work requirement in June 2018 which led to a sharp reduction in the Medicaid rolls. The policy affected only adult Medicaid enrollees, but the results shown below suggest that it may have had spillovers onto child enrollments even though it exempted adults with dependent children. Reports suggest that many of the thousands removed from the rolls were in fact employed and eligible, but unable to meet the work *reporting* requirements. These reporting requirements involved accessing computers and contacting the welfare office during regular work hours (Scott, 2018).

We control for two other important types of Medicaid and CHIP policies in our baseline models: premiums and income eligibility cutoffs. Four states reduced premiums from 2014 – 2020, and one (New Jersey) increased them very slightly.[8] Although some states have a schedule with different premiums for different income levels, we use values for the premium and enrollment fees for children at 201 percent of the federal poverty level, FPL (or 200 percent if that is the upper limit).[9] Premiums are coded in dollars at a monthly level – for example, if the premium is administered on an annual basis, its value is divided by 12. Because changes in premiums were so small, they seem unlikely to be a major factor in explaining changes in enrollments over time.

Data about child Medicaid and CHIP income eligibility cutoffs as a percent of the FPL is also included (KFF 2022a). In the analysis, we use the highest income limit for Medicaid or for separate CHIP programs for the age groups 0 to 1, 1 to 5, and 6 to 18. We code 100 percent of the federal poverty level as 100. Most states had either no change, or only small fluctuations in

[8] Data on premiums comes from KFF (2022a).

[9] Premium data is also available at 151, 251, 301 and 351 percent of the federal poverty level from KFF (2022a). We use 201 percent because at 151 percent of the federal poverty level children don't pay premiums in most states and at 251% and above children aren't eligible for either Medicaid or CHIP in many states. Idaho is the only state with a maximum income eligibility cutoff below 200 percent that has premiums. We use the premium level at the upper limit in Idaho, which ranges from 185 to 190 percent of the federal poverty level.

income limits, which is unsurprising given that federal "maintenance of effort" requirements in the Affordable Care Act forbade reductions in income cutoffs. However, Kansas reduced the real income eligibility cutoff by a total of 7.2% over the period by fixing the cutoff at the 2008 federal poverty level (adjusted in 2014) rather than using the FPL for each subsequent year (KFF, 2022a). Both premiums and income cutoffs are assumed to apply to state-specific fiscal years rather than calendar years.[10]

In what follows premium changes, income cutoffs, and work requirements are controlled for in the baseline specifications, but because the changes in income cutoffs and work requirements apply to few states, we test the robustness of the results to dropping Kansas and Arkansas. In addition, California expanded Medicaid eligibility to undocumented immigrant children in May 2016, which is likely to have increased Medicaid enrollments. Hence, robustness checks excluding California are also shown.

Finally, in an effort to ensure that important policy changes were not overlooked, we went through all of the policies collected by KFFs in their annual 50-state survey to identify any additional policies that saw changes in four or more states between 2014 and 2020. Since all models include state fixed effects, a policy has to have changed during our sample period in a number of states in order to be relevant for our analysis (although we make an exception for work requirements which changed in only one state, as discussed above). The policies included in additional analyses are: Coverage for lawfully-residing immigrant children without a five-year wait; real-time eligibility determination; presumptive eligibility; automated processing of

[10] We use income limit and premium data from 2011 for 2010 as this data is unavailable in 2010. Premium data from 2015 is used for 2014 as premium data is unavailable in 2014. According to KFF, Medicaid and CHIP policies remained constant across both of these time periods.

renewals; and the elimination of waiting periods for CHIP.[11] As shown below, these policies were not individually statistically significant determinants of enrollments and including them did not reduce the estimated effects of administrative burdens.

Figure 1 provides some examples of several large states that increased administrative burdens (Panel A) and several that did not (Panel B). All of the states saw initial increases in child enrollments beginning in 2014, especially those that initially froze redeterminations after the implementation of the Affordable Care Act. However, in Missouri, Colorado, Florida, and Tennessee, the figure shows that the subsequent implementation of new policies increasing administrative burdens corresponded to sharp declines in enrollments. The pattern for Tennessee is particularly striking since after the state rescinded the burdensome policy, enrollments resumed their upward trend. One can also see that the pandemic-era pause on redeterminations was associated with large increases in enrollments in all states.

<Figure 1 about here>

Given that there are many other factors that could have influenced enrollments, one would not want to draw inferences about the impact of the policies solely from inspection of these figures. Still, the patterns shown here certainly suggest that the policies may have had an important role, a hypothesis that is pursued more formally below.

C: ANNUAL SELF-REPORTED DATA ON MEDICAID AND CHIP ENROLLMENTS FROM THE AMERICAN COMMUNITY SURVEY

[11] We assume that this data applied to state-specific fiscal years in the same manner as the income eligibility limits and premiums. We use state values for Medicaid as CHIP-related policies in states without CHIP. We used data (if available) from 2015 for 2014 if data was unavailable in 2014.

The monthly Medicaid and CHIP enrollment data from Medicaid.gov is aggregated and is not stratified by children's characteristics such as race and ethnicity or citizenship status. Detailed data is not publicly available from most individual states either.[12] Hence, in order to address the question of who is most affected by administrative barriers, we turn to data from the ACS. The ACS asks about each child's Medicaid or CHIP coverage and about the characteristics of their households. The ACS data is annual and self-reported while the CMS data from Medicaid.gov is monthly and comes from administrative records. The level of public health insurance coverage is known to be under-reported in the ACS (Boudreaux et al., 2013), but aggregating the CMS data to the state-year level produces an annual time series with similar turning points and trends as are observed in the ACS data. The correlation coefficient for the two datasets from 2014 to 2019 is 0.83.

Aside from the fact that the ACS is annual, and that public health insurance coverage is likely understated, a third significant limitation of the ACS is that data collection for 2020 was disrupted by the COVID-19 pandemic and other factors, leading the Census Bureau to warn that the 2020 data may not be comparable to data for previous years. Pandemic disruptions were especially impactful for low-income respondents who are typically surveyed using in-person methods. These respondents are also more likely to use Medicaid or CHIP. The result is that the Medicaid and CHIP coverage rates in the 2020 ACS are inconsistent with data cross-checks to the Medicaid.gov enrollment data (U.S. Census Bureau, 2021). However, an advantage of the ACS data is that it is available for a longer time period. We therefore focus on the period 2010 to 2019 for analyses using the ACS data.

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[12] By publicly available, we mean that the data cannot be obtained without submitting a formal request to each state, possibly in the form of a Freedom of Information Act request, and that such requests would then be subject to state administrative review and possible denial.

The ACS data is used to examine the impact of the administrative burden policies by race, ethnicity, gender, age, poverty level, and whether the parents are non-citizens, non-college graduates, or have limited English proficiency. Respondents are able to choose as many options for “race” as they desire. Respondents who checked only “white” are coded as white and those who checked only “Black” as Black. All others are coded as “other” including those who check both white and Black. Hispanic ethnicity is coded as a separate variable in the ACS, and anyone who did not self-identify as Hispanic is treated as non-Hispanic. Respondents are asked about whether they are not able to speak English or whether they do speak English but “not well.” Information about the parents (i.e. English proficiency, citizenship, and education) is missing if the child does not live with at least one parent.[13] Means for the ACS sample are shown in Appendix Table A5.

II. Methods

In order to focus attention on the potential role of administrative burdens, we first present standard event study graphs using the CMS data and showing Medicaid and CHIP enrollments before and after these requirements were increased. The event study specification is written as follows:[14]

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[13] We drop observations if they have no data for poverty level or family income, family income exceeds 1 million dollars per year, or they do not live with a parent. Seven percent of the sample children fulfill these criteria. These children are disproportionately older: 34.5 percent are 18 compared to 6.5 percent in the sample of 0-18 year old children. Since this percent is higher for older children than for younger children, the estimates broken out by age also include a specification excluding 18-year-olds.

[14] Lags and leads are defined as:

$(Lag\ j)_{st} = 1[t = AdminBurdenEvent_s - j]$ for $j \in \{1, \dots, J-1\}$,

$(Lag\ J)_{st} = 1[t \le AdminBurdenEvent_s - J]$,

$(Lead\ k)_{st} = 1[t = AdminBurdenEvent_s + k]$ for $k \in \{1, \dots, K-1\}$,

$(Lead\ K)_{st} = 1[t \ge AdminBurdenEvent_s + K]$.

(1) $EnrollRate_{st}$

$$= \beta_0 + \sum_{j=2}^{J} \gamma_j (Lag\ j)_{st} + \sum_{k=1}^{K} \delta_k (Lead\ k)_{st} + \beta_1 WorkReqs_{st}$$

$$+ \beta_2 Premiums_{st} + \beta_3 RedeterminationPause_{st}$$

$$+ \beta_4 MedicaidExpansion_{st} + \beta_5 IncomeElig_{st} + \boldsymbol{X}_{st}\theta + \tau_t + \tau_s + \varepsilon_{st}$$

where for state *s* in month *t*, $EnrollRate_{st}$ indicates the monthly child Medicaid plus CHIP enrollment level divided by the estimated total population of children aged 0 to 18 in that state and year from the ACS. $AdminBurdenEvent_s$ is a variable recording the time *t* at which an increase in administrative burden is adopted in state *s*. The variables $WorkReqs_{st}$, $RedeterminationPause_{st}$, and $MedicaidExpansion_{st}$ take a value of 1 after a state implements the given policy change. $Premiums_{st}$ represents premium levels for one child and $IncomeElig_{st}$ represents maximum income eligibility cutoffs at a given state and time. $\boldsymbol{X}_{st}$ is a vector of state-level, time-varying controls for the unemployment rate, the child poverty rate, and gross state product.[15] The unemployment rate is available monthly while the child poverty rate and gross state product are available annually. State (τ_s) and time (τ_t) fixed effects are used to control for all fixed state and time-level determinants of child Medicaid and CHIP enrollment rates. Standard errors are clustered by state.

Event studies are estimated using three different balanced panels with the CMS data from 2014 to 2020. The first, keeps all 14 states that experienced administrative burden increases over this time period and includes 9 leads and 16 lags. The second, keeps only states that had

[15] The unemployment rate control is seasonally adjusted monthly unemployment rates from the Bureau of Labor Statistics. The gross state product per capita control is the annual all industry real gross domestic product in billions of chained 2012 dollars from the Bureau of Economic Analysis divided by the total population in each state calculated using the ACS. The poverty rate is calculated as the weighted proportion of children under 19 in the ACS that live in a family with income below the federal poverty level, where 100 would represent 100 percent of poverty.

sufficient data to include 13 leads and 17 lags, which means that Texas and Oklahoma are dropped. And in the third sample, only states with 34 leads and 23 lags are included which leaves nine states: Colorado, Florida, Hawaii, Idaho, Illinois, Louisiana, Mississippi, Missouri, and Tennessee.[16]

The event studies are followed by a regression analysis of the relationship between all the policy changes and combined monthly Medicaid and CHIP enrollment rates in the CMS data which is estimated using the following equation:

$$
\begin{aligned}
(2)\ EnrollRate_{st} &= \beta_0 + \beta_1 AdminBurden_{st} + \beta_2 WorkReqs_{st} + \beta_3 Premiums_{st} \\
&+ \beta_4 RedeterminationPause_{st} + \beta_5 MedicaidExpansion_{st} \\
&+ \beta_6 IncomeElig_{st} + \boldsymbol{X}_{st}\theta + \tau_t + \tau_s + \varepsilon_{st}
\end{aligned}
$$

This specification replaces the lag and lead variables from equation (1) with the variable $AdminBurden_{st}$ which takes a value of 1 after an administrative burden increase was implemented in a state. Standard errors are again clustered by state. A similar specification is used to estimate the impact of policy changes on enrollment churn. Each variable is aggregated to the annual level and enrollment churn is treated as the dependent variable, but otherwise the model is the same as (2) with a different dependent variable.[17] This specification is also used for additional models including one that breaks the administrative burden variable into two components, and models that add additional measures of state policies from the KFF surveys.

[16] Although in our dataset the administrative burden change has an end date in Tennessee and Louisiana, we treat the policy change as irreversible in this event study specification. We use the first policy change in the case of Louisiana where there are two.

[17] Policies "turn on" if in place for at least half of the year.

Recently, the econometrics literature has described challenges in drawing inferences from difference-in-difference or event study estimates in the presence of variations in the timing of treatments and/or heterogeneity in treatment effects (Callaway and Sant'Anna, 2021; Sun and Abraham, 2021; Goodman-Bacon, 2021). In order to address these challenges and investigate the robustness of the estimates, the analysis of the impact of administrative burden on combined Medicaid and CHIP enrollment rates is repeated using the approach suggested by Callaway and Sant'Anna (2021). The first step is to generate average treatment effect estimates for each group of states in which an increase in administrative burden took effect at the same time. Covariates cannot be included in this specification due to the small size of each of these groups. Standard errors are clustered by state. Since these procedures do not work well with missing data, the sample here starts in September 2014 and drops data for two "control" states (New Mexico and California) and one treatment state (Ohio).

These group-year estimates can be presented in three different ways: As a simple weighted average, as group-specific time averaged effects, and as dynamic effects. The first two can be compared to the standard difference-in-difference estimates, while the third can be used to generate figures analogous to the event studies. The simple aggregation is the average of all the group-time average treatment effect estimates, weighted by group size. The group-specific effect is the effect for all states where administrative burdens were implemented in the same month, averaged over all time periods after treatment. The dynamic effects produce the effect relative to the policy implementation time. Three different panels are used to examine dynamic effects, balancing each panel across different lengths of exposure to the treatment. The first uses 16 lags and 47 states. The second uses 17 lags and drops Oklahoma. The third uses 23 lags and drops Montana and Oklahoma.

One limitation of the CMS Medicaid and CHIP enrollment files is that they do not include any information about the socio-demographic characteristics of the enrolled children. In order to examine the impact of changes in Medicaid and CHIP enrollment on specific groups of children, we turn to the annual ACS data. The baseline estimated models take the following form:

$$(3)\ Enroll_{ist} = \beta_0 + \beta_1 AdminBurden_{st-1} + \beta_2 WorkReqs_{st-1} + \beta_3 Premiums_{st-1} + \beta_4 RedeterminationPause_{st-1} + \beta_5 MedicaidExpansion_{st-1} + \beta_6 IncomeElig_{st-1} + \boldsymbol{X}_{st-1}\theta + \boldsymbol{Z}_{ist}\gamma + \tau_t + \tau_s + \varepsilon_{st}$$

where *i* indexes the individual child, *s* refers to state and *t* refers to year. The variables are defined as in (2) with the exception of $\boldsymbol{Z}_{ist}$ which is a vector of individual child-level characteristics including indicators for Hispanic ethnicity, race (white, Black or other); gender; age (Infant, 1-5, 6-11, or 12 and above); total family income (in thousands, adjusted for inflation); highest parent education (high school, some college or college and above); and indicators for whether the child has a non-citizen parent or a parent who does not speak English well. Because the data is annual, a child could have been surveyed before or after a policy change in that year, resulting in a great deal of measurement error. Hence, we lag policy changes and other state-level variables by one year so that all children surveyed in a given year would have been affected by the policy.[18] Standard errors are clustered by state to allow for correlations in errors within states.

[18] Note that this means that the ACS observations for children from 2010 are not part of the benchmark regressions, as our policy data starts in 2010 and is lagged by one year.

We also estimate models including interactions between the indicator for self-reported Hispanic ethnicity and the beginning of the Trump administration in 2016, and an interaction of the indicator for Hispanic with an indicator for the year following the announcement of the new public charge rule. The idea is to see whether the estimated effects of the administrative burden variables are confounded by these national-level events, which are likely to have had a disproportionate impact on Hispanic children. KFF reports that in a survey of health centers, 28 percent reported that immigrant parents have been disenrolling their children from Medicaid (Tolbert et al., 2019). The Urban Institute found that in 2018, one in five Hispanic families with immigrant members reported that they avoided using public benefits and 42 percent of these respondents said that someone in their household was avoiding using Medicaid or CHIP (Bernstein et al., 2019). Note that the main effect of both policies will be absorbed by the year fixed effects included in the models, which is why we are focusing on the interactions with the indicator for being Hispanic.

Finally, models of the form (3) are estimated for each subgroup of children; that is, by race/ethnicity, income category, characteristics of parents (college vs. non-college, citizen vs. non-citizen, weak English vs. non-weak English), and child age. These regressions are used to ask whether the administrative burdens have greater effects on the enrollments of some groups of children compared to others.

III. Results

A. EVENT STUDIES

Figure 2 shows the three standard event study graphs discussed above. These graphs tell a consistent story even though they are based on slightly different samples of states. In each case, enrollments are flat prior to the change, and then start to trend downwards immediately after the increases in administrative burden. The differences become statistically significant by two months after the change for Panels A and B and three months for Panel C. The graphs suggest that post-treatment enrollments remain significantly lower than in the period before the policy changes.

<Figure 2 about here>

Figure 3 shows event study estimates based on the Callaway and Sant'Anna (2021) method described above. These figures show a similar pattern. Enrollment is flat for more than 4 years prior to the policy change and then begins to trend downwards immediately after administrative burdens are implemented. The estimates become statistically significant by about four months after implementation and remain significantly lower.

<Figure 3 about here>

B. ESTIMATED EFFECTS OF POLICIES ON MONTHLY ENROLLMENTS

Table 2 shows estimates of equation (2). The first column shows the baseline regression, estimated using monthly CMS administrative enrollment data from 2014-2020. The estimates suggest that increases in administrative burden reduce Medicaid plus CHIP enrollments by 1.7 percentage points. Column (1) also suggests that higher income cutoffs increased enrollments, while higher premiums and work requirements decreased them. We do not find significant effects of redetermination pauses and Medicaid expansions, possibly because the time period begins in 2014 (so that changes between 2013 and 2014 cannot be included) and the remaining effects of these policies are absorbed by the state and year effects included in the models. The child poverty rate, unemployment rate, and gross state product per capita are also not statistically significant.

<Table 2 about here>

The model shown in Column 2 splits the administrative burden variable into the two types of policies discussed above: Policies that increased the frequency or stringency of income or eligibility checks, and automatic disenrollment policies. Column 2 shows that the point estimates of these two types of policies are almost identical. Appendix Table 2 explores the lagged effect of these two types of policies. This table suggests that by 12 months after the policy change, automatic disenrollment may be having a larger impact and that the impact of more frequent or stringent eligibility checks diminishes over time, though it still not possible for us to reject that the two types of policies have similar impact. Hence, the rest of the paper focuses on one pooled administrative burden variable.

Column 3 of Table 2 shows that the estimated coefficients on the policy variables are very similar with or without the indicators of aggregate state-year level macroeconomic conditions. This finding is unsurprising given that state and year indicators are included in the regressions and suggests that the results are not biased by the omission of additional macroeconomic controls. Column 4 shows models estimated over the period 2014 to 2019. It is reassuring to see that the point estimates including the pandemic are qualitatively similar to those estimated for the 2014 to 2020 period.

Column 5 of Table 2 shows the impact of each variable on enrollment churn. Administrative burden increases enrollment churn by 5.7 percentage points but we do not find statistically significant effects of the other policies. This result suggests that administrative burden not only decreased overall enrollment rates, but also increased the share of enrollees cycling in and out of Medicaid or CHIP coverage.

The event study graphs indicated that it took some time for the full impact of the policy changes to be felt. Table 3 explores this issue by using policy variables measured using 6, 12, 18 and 24-month lags. Table 3 suggests that the impact of administrative burden grows in the first year, and then begins to decline. For example, increases in administrative burden that occurred six months before are associated with an enrollment reduction of 2.5 percentage points compared to 1.7 percentage points for the instantaneous policy change.

<Table 3 about here>

Table 4 presents aggregated estimation results using the Callaway and Sant'Anna (2021) approach. The first row shows the simple weighted average of all group-time average treatment effects. It is significantly negative and larger than the baseline estimate discussed above. The rows below show the average treatment effect for each group of states whose policies began at the same time. The results are negative in ten out of eleven groups and are statistically significant and negative in seven groups. The point estimates for the individual groups of states suggest that policies implemented in Arkansas, Idaho, and Tennessee may have had the largest effects.

<Table 4 about here>

C. ESTIMATED EFFECTS OF ADMINISTRATIVE BURDEN USING INDIVIDUAL-LEVEL ANNUAL SELF-REPORTED ACS DATA

This section of the paper uses ACS data from the U.S. Census to ask how children from different socioeconomic backgrounds are impacted by policies that increased administrative burdens. However, Table 5 first shows estimates of equation (3) including all children to benchmark the ACS estimates with those using the monthly CMS data.

<Table 5 about here>

Table 5 shows that increases in administrative burden are associated with a statistically significant drop in the probability that a child is covered by Medicaid or CHIP. The estimated coefficient of -0.0087 is smaller than that obtained in the CMS data (-0.0172), which may be because of the attenuation bias stemming from the known measurement error in the ACS data. Hence, the comparison suggests that estimates using the ACS may understate the true sensitivity of individual enrollments to policy changes and should be interpreted with that caveat in mind.

The rest of Table 5 shows that the estimates are robust to changes in specification including dropping the other state-level covariates or including data from 2020. The last two columns add interactions of the indicator for Hispanic ethnicity with, respectively, an indicator for the years of the Trump administration, and an indicator for the year after the new public charge rule was announced.

The former is not statistically significant, but the interaction with the public charge rule is large and statistically significant. The estimates indicate that Hispanic children had a 7.0 percentage point higher probability of being enrolled at baseline but that after the announcement of the new public charge rule, their probability of being enrolled dropped by 1.8 percentage points.[19] Importantly, the inclusion of this interaction does not change the estimated impact of the administrative burden variable.

Recall that an important advantage of the ACS data is that we can include data from before 2014. Accordingly, these models are estimated using data from 2010 to 2019.[20] This

[19] Barofsky et al. (2020) study the effects of a national announcement in September 2018 that Medicaid use could affect a family's immigration status using data from 5 states. They find that counties with higher non-citizen shares experienced larger post-announcement declines in child Medicaid enrollments. Unfortunately, we do not have national county-level data on enrollments.

means that we can capture both the initial effect of Medicaid expansion in 2014, and changes that many states made to their income cutoffs for Medicaid and CHIP in 2013. The table shows that Medicaid expansion had a positive effect on enrollments that is approximately equal in absolute value to the negative effect of imposing administrative burdens. The sign of the estimated effect on the maximum income cutoff seems counterintuitive, but it is small. It is possible that it reflects other changes in Medicaid and CHIP programs that states made in the run-up to the implementation of the ACA. The estimates also indicate that Black children, children of other race, younger children, children with less educated parents, children with non-citizen parents and children whose parents do not speak English well are more likely to be enrolled, other things being equal.

Table 6 shows estimates of the effect of administrative burden from the individual-level ACS data stratified by group. Each coefficient is from a separate regression. The first panel shows estimates by race and ethnicity. These regressions suggest that the estimated effect of administrative burdens is more than three and a half times as large for Hispanic children as for non-Hispanic children.

<Table 6 about here>

The second panel of Table 6 breaks down the estimated effects by income. These estimates suggest that administrative burdens had the largest impact on the poorest households and on households with incomes between 200 and 400 percent of the federal poverty level. These findings likely reflect different mechanisms—it is possible that the poorest families struggle to meet the new administrative requirements. For example, informal workers may find it difficult to provide proof of income. People in the 200 to 400 percent of the federal poverty level may be more influenced by the additional costs of obtaining coverage relative to the perceived benefits.

The third panel of Table 6 breaks the sample down by characteristics of parents. These breakdowns show that the effects of administrative burdens are greater in households in which no parent has a college degree, and that the estimated effects are three and a half times greater for children with a non-citizen parent compared to children with citizen parents. Similarly, children with a parent who reports weak English skills are more likely than other children to be affected by administrative burden.

Finally, the fourth panel of Table 6 shows estimates by child age. These estimates suggest that the effects of administrative burden are similar for children of all ages. While in principle, infants should receive one year of coverage if their deliveries were paid for by Medicaid, these estimates suggest that stricter eligibility requirements and automatic disenrollment policies are being applied to them as well.[21]

D. ROBUSTNESS CHECKS

Appendix Table 3 shows estimates of the effects of the policy variables on CMS monthly administrative Medicaid and CHIP enrollments from 2014-2020 estimated on samples that exclude Kansas, Arkansas, and California, as discussed above. The estimates are very similar to those in Table 2. We also show estimates excluding Idaho, because the exact date when it adopted stricter paperwork requirements that increased administrative burden is not completely

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[21] For example, in Texas, the state Health and Human Services web site notes that applications for CHIP perinatal benefits are commonly denied if women do not check every box on the form, even if the appropriate answer is n/a. Applications are also denied if the application is not signed or if any missing documents are not sent in quickly enough. https://www.hhs.texas.gov/providers/health-services-providers/chip-perinatal-providers/chip-perinatal-faqs#:~:text=Following%20delivery%2C%20most%20babies%20born,that%20specifies%20CHIP%20Perinatal%20Program.

clear (see Appendix Table 1 for more details). Again, this has relatively little effect on the estimates.

Appendix Table 4 shows estimates of models similar to those in Table 2 but adding additional policy measures from KFF. Some measures are not available for all years, which creates smaller samples in some cases. The estimates show that none of the policies are individually statistically significant. When all the policies are included, real time eligibility determination is estimated to have a negative effect, but it is not clear how much weight should be placed on this result given that adding only this policy (column 5) does not indicate a statistically significant effect. Importantly, including these additional policy variables either leaves the estimated effect of the administrative burden variable unchanged, or increases it.[22]

Appendix Table 6 shows models using ACS data which are similar to those in Table 5, except that they show the impact of lagging the administrative burden variable. The estimates suggest that the effects are greater with a two-year lag, and that they are detectable four years after a policy change that increases administrative burden.

Appendix Table 7 shows estimates from models similar to those in Table 6, but using an indicator for whether the child has *any* health insurance as the dependent variable rather than whether they have public health insurance coverage. If losses of public health insurance coverage were made up by increases in private health insurance coverage, then the estimated effects of administrative burden would be smaller in these models. We see for example, that increases in administrative burden reduced public health insurance for all children by 0.9 percentage points, but that the reduction in having any health insurance is only 0.6 percentage

[22] Other policies that have been shown to be important for Medicaid enrollments include Medicaid physician payments which are usually less than those from private insurers (Hahn, 2013; Alexander and Schnell, 2019) and Medicaid managed care penetration rates (Currie and Fahr, 2005). However, the former is not readily available in each year and the later has shown little variation over time in recent years.

points. However, for Hispanic children, the loss of public health insurance was less likely to have been replaced: We see a decline of 1.8 percentage points in public health insurance coverage compared to a 1.4 percentage point decline in the probability of reporting any health insurance coverage. Looking by income suggests that when children from the poorest families lose public health insurance coverage due to increases in administrative burden, they are not able to replace it with private health insurance. Similarly, children whose parents did not go to college, are non-citizens, or have weak English are unable to make up losses in public health insurance coverage with private insurance.[23]

IV. Discussion and Conclusions

Our estimates suggest that, conditional on other policy changes that affected Medicaid and CHIP enrollments, increases in administrative burden in some states were responsible for an initial overall national enrollment decline of 1.7 percentage points, or 4.0% nationally. The magnitude of these impacts tended to grow over time reaching a peak decline of 2.5 percentage points or 5.9% in the year after the policy change. Event study analyses suggest that these negative effects were sustained for at least two years after the policy changes. Using newer difference-in-difference and event study methods suggest that these regression-based estimates are conservative and that the true magnitudes could be even greater. Importantly, while we find separate effects of the new public charge rule, accounting for it does not reduce the estimated impact of administrative burden. The estimated negative impacts of administrative burden on children's public health insurance enrollments are also robust to excluding different

[23] Table 6 showed a very small and insignificant effect of administrative burden on families with incomes over 400% of poverty. The equivalent coefficient in Table A7 is even smaller, but statistically significant suggesting that there may be a small number of relatively high-income families who are affected. Measurement error in self-reported insurance status as well as in incomes around the 400% of poverty threshold may also be a factor.

combinations of states, to using either administrative or survey data, and to using different estimation methods.

While the annual, individual-level, self-reported ACS data on Medicaid and CHIP enrollments is imperfect in that it understates enrollments, estimates using the ACS suggest that the impact of increased administrative burden was unevenly distributed. The estimated effects are more than three and a half times as large for Hispanic compared to non-Hispanic children, four times greater for children who have a parent who does not speak English well, and three and a half times greater for children with a non-citizen parent compared to children with citizen parents. Regarding this latter finding, it is worth noting that the vast majority of U.S. children with a non-citizen parent are U.S. citizens, and therefore entitled to services.[24]

These findings are subject to several limitations. First, it would be desirable to directly examine the impact of state policy changes on the verified *monthly* Medicaid and CHIP enrollments of individual children, or at least on the enrollments of demographically defined groups of children. However, this is not feasible nationally using publicly available data sources.[25]

Second, our measures capture only *official* changes in administrative burdens. Unofficial burdens such as losing people's paperwork, requiring them to come back with documents that are not actually required, giving misinformation, or making it impossible to contact officials are more difficult to quantify, though they are known to happen (Heinrich et al.

[24] In families with an unauthorized non-citizen parent, 80% of the children are U.S. citizens (Capps et al., 2016).

[25] It is not possible to do this analysis using the confidential individual-level claims files from the Center for Medicare and Medicaid Services (which researchers can apply to have access to) because the format of these files changed over time. Up to 2015, the files available are the Medicaid Analytic eXtract or MAX files. After 2015, CMS switched to The Transformed Medicaid Statistical Information System (T-MSIS) Analytic Files (TAF). In addition to different data elements, the TAF files for the first several years were incomplete.

2022). Hence, our estimates are likely to under-state the true negative impacts of administrative burdens on enrollment.

These results provide new evidence about the importance of recent changes in administrative burdens and resulting reductions in children's enrollments in public health insurance. These reductions occurred over a period in which eligibility requirements, income cutoffs, and CHIP premiums remained largely unchanged due to maintenance of effort requirements imposed on states by the federal government under the Affordable Care Act. Moreover, other factors such as the expansion of Medicaid to low-income adults and redetermination pauses tended to increase child enrollments and so offset the negative impact of the increases in administrative burdens to some extent.

Renewed attention to the impacts of administrative burdens on enrollments in public health insurance is particularly timely now that the public health emergency declared at the start of the COVID-19 pandemic has ended. Beginning in March 2020, states were required to suspend disenrollment from Medicaid for the duration of the emergency, with the result that the caseload grew by over 20 percent (Corallo and Moreno, 2023). Now eligibility will need to be re-determined for more of these people, with the result that the administrative changes implemented prior to the pandemic may have more bite. The huge backlog of redetermination cases may have its own negative impact on the timeliness and accuracy of re-enrollments. Going forward, some of the policies states are implementing to deal with redeterminations are similar to the policies studied here. For example, twelve states redetermination plans include terminating benefits without notice (Tolbert and Ammula, 2023). Given the demonstrated importance and cost-effectiveness of public health insurance coverage for children, the federal government may wish to take steps to address the negative consequences of administrative burden on children's enrollment in public health insurance.

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FIGURE INFORMATION

Figure 1:
Title: Child Medicaid Plus CHIP enrollments in states with (Panel A) and without (Panel B) policies that increased administrative burdens
Legend: The figure shows administrative Medicaid and CHIP enrollment for children over time. The solid vertical black line indicates the start of an increase in administrative burden, while the dotted vertical black line indicates the end of an increase in administrative burden. Shaded lines show pauses in Medicaid and CHIP redeterminations.

Figure 2:
Title: Event Study of the Effect of New Administrative Burden on Child Medicaid Enrollment
Legend: We report ordinary least squares coefficient estimates and their 95 percent confidence intervals, clustering at the state level. Panels indicate all-state sample (panel A), 48-state sample (panel B) and 45-state sample (panel C).

Figure 3:

Title: Event Study Following Callaway and Sant'Anna

Legend: Black lines give point estimates and uniform 95% confidence bands for pre-treatment periods and gray lines provide point estimates and uniform 95% confidence bands for the treatment effect of increasing administrative burden. We cluster at the state level. Panels indicate a sample of 47 states (panel A), 46 states (panel B), and 45 states (panel C).