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ABSTRACT

We examine how Medicaid expansion under the Affordable Care Act reshaped federal transfer inflows to counties using state Medicaid expansions between 2014 and 2017. We show that the ACA expansion increased federal Medicaid transfers by $361 per capita in expansion counties. Using our estimates, we forecast that non-expansion counties would gain $554 per capita if they expanded Medicaid. These transfers flow to counties with lower tax capacity and lower gross income. Our findings suggest that Medicaid expansion was a health policy intervention that also functioned as a budgetary mechanism reshaping federal to local transfers and fiscal smoothing across U.S. counties.

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1 Introduction

Medicaid has become the largest single source of intergovernmental revenue in state and local budgets (Pew Charitable Trusts, 2025; Kaiser Family Foundation, 2025b). In fiscal year 2023, the program spent roughly $894 billion, with 69 percent from federal funds and 31 percent from states. Enrollment remains near historic highs following the public health emergency policy that automatically suspended disenrollment from 2020 to 2023. National Medicaid and CHIP enrollment stood at about 77 million in September 2025, down from an unprecedented peak of 94 million during the continuous-coverage period in early 2023 (Centers for Medicare & Medicaid Services, 2025; Kaiser Family Foundation, 2025a). Beyond providing insurance and financing healthcare for people with low income, Medicaid can stabilize local government budgets during downturns, easing fiscal strain when the economy deteriorates (Perez et al., 2021).

In this paper, we estimate the effects of the ACA Medicaid expansion on federal transfer spending at the county level using a difference in difference strategy that allows the treatment effect to vary with each county's baseline share of newly eligible residents. Our estimates imply that expanding Medicaid to all states as intended would have increased annual federal transfers by $456 per capita in the average county. The effect varies substantially across counties. In expansion states, the average county receives $361 per capita in additional federal Medicaid transfers. Forecasting expansion effects for counties in non-expansion states, we find the average county would receive $554 per capita.[1]

We combine our estimates of county-level federal Medicaid transfers with IRS data on federal income tax contributions and adjusted gross income per capita. In expansion states, the top 20% of counties by federal Medicaid receipts were disproportionately in the bottom 20% by state tax contributions to the program. We also find a strong negative association between ACA-induced transfers and both historical income tax contributions

[1]The full county-level dataset, including the 2010 newly eligible share variable and four county-level treatment effect variables (one for each specification), is available at https://github.com/lmontenovo1/ACA_county_treatmenteffects.

and AGI at the county level. The expansion functioned progressively: larger per-capita transfers flowed to counties with lower incomes and smaller tax contributions.

Finally, we translate our estimates of ACA-induced county Medicaid transfers into implied enrollment increases using a simple back-of-the-envelope calculation: we divide estimated transfer effects by average federal per-enrollee expenditures. We then cross-check these county-level enrollment estimates by aggregating them to the state level and comparing them with administrative enrollment figures reported by CMS. The two series track closely, validating our approach. Our estimates imply that if the ACA expansion were implemented nationwide, the average county would gain about 7,325 new Medicaid enrollees, translating to roughly 7 percent of the average county's population. The large standard deviation indicates substantial heterogeneity across the country.

Systematic use of county-level Medicaid enrollment data remains rare, reflecting persistent gaps in publicly available sub-state records.[2] Early work by Barker et al. (2017) was the first to assemble county-level enrollment data by collecting administrative records directly from states, documenting substantial rural–urban heterogeneity in enrollment growth following the ACA. Subsequent work extended this approach to examine changes in enrollment composition and managed care participation at sub-state levels (Li et al., 2018). Most empirical analyses, however, continue to rely on state-level aggregates or proxy measures. Our transfer-based estimates offer a way to characterize geographic heterogeneity in the ACA expansion's enrollment effects without requiring county-level administrative data. To our knowledge, this is the first attempt to systematically quantify local-level fiscal redistribution patterns triggered by the ACA using county-level fiscal data.

The ACA is a multifaceted reform that affected coverage and health through several

[2]The Census Bureau's Small Area Health Insurance Estimates (SAHIE) project provides annual county-level estimates of overall health insurance coverage from any source. But SAHIE does not report county level Medicaid enrollment specifically. CMS reports state-level administrative enrollment totals at https://www.medicaid.gov/medicaid/national-medicaid-chip-program-information/medicaid-chip-enrollment-data/index.html but does not provide county-level data.

avenues. Despite the complexity, an extensive literature has considered the impacts of the Medicaid expansions, exploiting the state-level adoption decision, on a wide range of health insurance, health and labor market outcomes (Gruber and Sommers, 2019; Soni et al., 2020; Peng et al., 2020).

Similarly, there has been much interest among policy economists to understand the fiscal and spending implications of the Medicaid expansion. However, this literature is still small and primarily descriptive. At an aggregate level, the Congressional Budget Office (CBO) (CBO, 2019) provides forecasts of federal Medicaid spending, including their expectations on future expansion states or projections of health insurance coverage and health insurance costs net of federal subsidies up to year 2030 (CBO, 2018). The CBO forecasts show estimates at the federal level or, at most, separately by expansion status. At a more granular level, prior works overall suggest that expanding states have not experienced changes in state-level funds nor reductions in spending on education or other programs (Gruber and Sommers, 2019, 2020; Levy et al., 2020; Buettgens, 2018).

While prior papers have estimated the county-level numbers of individuals newly eligible to Medicaid as a result of the ACA, these analyses are not very informative about the dollar transfers to these counties, as the costs vary greatly by the county-level average characteristics of the beneficiaries.[3] However, none of these studies examines federal Medicaid transfer spending, paving the way for our contribution. Neither do they investigate the distribution of expansion-related expenditures at the county level or any other level of sub-state geography.

Our estimates also speak to debates about program take-up: counties with the largest potential fiscal benefits from expansion are disproportionately located in non-expansion states, suggesting that partisan and administrative factors dominate state adoption decisions over expected financial gains (Currie, 2006; Haeder and Weimer, 2015)

Our study quantifies the way the ACA Medicaid expansion redirected federal tax dol-

[3]This is a result of the health spending skewness Deb and Norton (2018).

lars toward economically disadvantaged counties, reshaping local fiscal capacity and redistribution. In doing so, the paper extends the public budgeting and finance literature by demonstrating how a major federal entitlement program functions as an intergovernmental grant mechanism with implications for fiscal structure.

2 Background on the ACA

The ACA aimed at increasing insurance coverage primarily through an individual mandate, extended dependent coverage for young adults, subsidies for private coverage, and expanded state Medicaid programs. A significant setback for the ACA occurred in 2012, when the US Supreme Court ruled that the Medicaid expansion was unconstitutionally coercive because it made funding for the original Medicaid program conditional on the adoption of the new ACA Medicaid provisions. The decision – in essence – gave states the choice to opt out of the ACA's Medicaid expansion. Between 2014 and 2018, 27 states expanded Medicaid in 2014, three in 2015, and two in 2016, shaping the treatment and control groups in our analysis. Figure I shows the Medicaid expansion unfolding across US states until 2017.

Frequent changes to Medicaid policy highlight its importance for fiscal capacity, making it essential to understand its effects on budgeting and stability. The resulting state-level variation in expansion decisions generated a quasi-experimental setting, which we use in this paper to explore the county-level fiscal implications of the ACA Medicaid expansion.

The conventional Medicaid program is jointly financed by the federal and state governments, according to the Federal Medicaid Assistance Percentage (FMAP) sharing rules. The federal government more generously finances the ACA expansions, which pays 100% of the costs of covering the newly eligible population for the first three years of the expansion, and then gradually reduces its share to 90% of the expenses in 2020 and thereafter.[4] More details on Medicaid program funding over time and by geography are in Rudowitz (2016), Donohue et al. (2022), and Dague and Ukert (2024). Often-cited concerns among non-expanding states are the costs of expansion and the implications of those costs for state budgets and other spending priorities (Krauss, 2009).[5]

3 Related Literature

An extensive literature has exploited the variation in state Medicaid decisions to understand how the expansions have affected insurance coverage and other outcomes. Gruber and Sommers (2019) and Soni et al. (2020), among others, review the literature on the ACA and find that the health reform led to substantial increases in insurance coverage and improved health outcomes. Similar conclusions are in Han et al. (2017) and Frean et al. (2017), estimating that Medicaid expansions have been responsible for most of the insurance coverage gains associated with the ACA across the country. Other research has explored the effects of the Medicaid expansion on employment and wages (Peng et al., 2020). While the health outcomes literature is vast, the budgetary and intergovernmental finance implications of Medicaid expansion remain comparatively underexplored. Further, much of this work is descriptive and at the state level, leaving a gap in understanding how federal transfers translate into fiscal resources at the county level — a core concern in public budgeting.

Some previous works focused on the fiscal and budgetary implications for hospitals.

[4]The costs associated with populations covered under the pre-ACA Medicaid program, including any ACA-induced "welcome mat" effects that boosted enrollment among previously-eligible people, would continue to be funded jointly by the federal and state governments according to the standard FMAP and not the enhanced ACA rate.

[5]Sommers and Epstein (2013) compiled information on state governors' opinions of the Medicaid expansions shortly after the 2012 election, on the eve of the ACA enactment. They report that 12 of 13 governors who opposed the expansion cited concerns about how the expansion would affect their state's budget. Among 20 governors who were undecided about whether to support the expansion, another 11 were also concerned about their state's budget.

Perez et al. (2024) use data from the Annual Survey of State and Local Government Finances and find that ACA Medicaid expansions increase local government spending on hospitals in geographical areas where voters are more supportive of the ACA. Blavin and Ramos (2021) examines the financial implications of the ACA Medicaid expansions on hospital finances. Their results highlight large financial benefits among hospitals in expansion states, with effect sizes varying by location, size, profit status, and safety-net status of hospitals. In a study addressing a similar research question, Rhodes et al. (2020) also finds enhancements in hospitals' financial outcomes, with larger effects in states with the greater increase in program eligibility, public hospitals, and in rural areas. Foutz et al. (2017) also highlighted urban-rural differences in the usage of Medicaid-covered healthcare. These studies emphasize provider finances, but stop short of examining the fiscal position of local governments themselves.

Other literature examines fiscal implications for states, mostly focusing on expansion states. Gruber and Sommers (2020) use annual expenditure reports provided by the National Association of State Budget Officers (NASBO) to study how ACA expansions affect state Medicaid and non-Medicaid spending. They find that most of the increase in Medicaid expenditures in expansion states is due to new funding from the federal government and that there is little evidence that this increased spending "crowds out" state spending on other areas of social policy. They also show that, at the state level, the rise in Medicaid spending is associated with pre-ACA uninsurance rates. Sommers and Gruber (2017) uses data for fiscal years 2010 to 2015 from the National Association of State Budget Officers and applies a difference-in-differences method to estimate the spending effects of the expansion. They find that the expansion increased overall Medicaid spending by 11.7 percent and spending from federal funds by 12.2 percent, but they detected no change in state funds. nor reductions of spending on education or other programs. Bachrach et al. (2016) examines annual budgets in 11 expansion states and finds that Medicaid expansion states have saved money because they receive more generous federal matching rates for newly eligible people who were previously receiving limited Medicaid support through waiver programs or other state programs. In addition, most states gain additional revenue from taxes levied on the revenues of health care providers and health plans, both of which grew because of the ACA expansion. This evidence suggests Medicaid expansions strengthen state fiscal capacity without forcing major tradeoffs — an important budgeting insight.

While most prior studies assess coverage and health outcomes, the public finance literature stresses intergovernmental transfers as both stabilizers and redistributive tools (Musgrave, 1959; Warner, 2001; Bahl et al., 2002; Clemens and Veuger, 2023). Indeed, FMAP increases have been a recurring federal stabilization instrument, featuring in fiscal responses to the tech crash, financial crisis, and pandemic (Clemens et al., 2021). Clemens et al. (2021) note that the geographic distribution of enhanced FMAP funds during the pandemic did not closely track the severity of local economic shocks, raising questions about how well Medicaid's financing structure achieves stabilization goals. Our work bridges the health and public finance literatures by showing how the ACA Medicaid expansion altered local fiscal resources and redistributive flows—evidence relevant both to the program's redistributive function and to understanding the baseline distribution of funds when FMAP-bump policies are deployed.

These general conclusions also emerge from a detailed modeling study of economic benefits from Michigan's Medicaid expansion (Ayanian et al., 2017; Levy et al., 2020), and from interviews with state budget officials at early stages of expansion (Dorn et al., 2015). National simulation modeling of benefits for states that have not yet expanded Medicaid reaches similar conclusions (Buettgens, 2018; Simpson, 2020). Gruber and Sommers (2019) review the literature on the ACA and conclude that the expansions do not appear to add to state budget pressures, and that the total ACA cost to the federal government up to 2018 was lower than expected.

There is a large literature on the distribution of federal spending and taxes (e.g., see

Splinter et al. (2020) and Looney et al. (2020) for recent examples). The basic theory of fiscal federalism suggests that efforts to redistribute income should be a responsibility of the central (rather than local) government because the social welfare benefits of redistribution will often accrue partly to people living outside of local jurisdictions, and because local efforts at redistribution may distort the migration incentives of people who pay taxes or receive benefits (Musgrave, 1959; Ladd and Doolittle, 1982). However, there is also a smaller literature on the redistributive implications of spending at state and local levels (Bahl et al., 2002). Warner (2001) compares federal transfers to counties with state transfers to counties. She finds that the amount and progressivity of redistribution are greater when transfers to counties come from state rather than federal aid. Clemens and Ippolito (2018) examine the conceptual foundations and implications of alternative federal matching formulas for the distribution of support for the Medicaid program.

Often, county receipts of federal spending in social programs are the right-hand-side variables in studies that examine the effects of spending on individual-level outcomes, such as effects of Head Start program spending on child mortality (Ludwig and Miller, 2007) or food assistance public spending impacts on total food spending (Hoynes and Schanzenbach, 2009). Research in political science has also tackled determinants of federal spending. Berry et al. (2010) uses data on federal transfers during different presidential administrations and finds that counties benefit from more federal transfers when they are represented by legislators in the president's party; later work on the same question using data through 2014 finds that this occurs mainly when the electorate favors public spending (Reingewertz and Baskaran, 2020).Similarly, Clemens and Veuger (2021) find that over-represented states received more generous per capita funding from pandemic relief legislation, with additional partisan effects under unified party control

A literature within economics examines how the business cycle affects transfer spending (Boylan et al., 2017; Fishback et al., 2005). One line of work that is closely related to ours is the literature on how local transfers are shaped by state policy changes. For example, Murray et al. (1998) examine the effects of state-financed educational reform on the equality of local resources within a state.

However, none of these studies examines federal Medicaid transfer spending at the local level within expansion and non-expansion states, or investigates the distribution of expansion-related expenditures at sub-state geography, the focus in this paper.

4 Data

We examine the effects of state-level ACA Medicaid expansions on how federal Medicaid funds are channelled to resident populations in nearly all counties in the United States. Throughout the paper, we adopt the geographic definitions that the Bureau of Economic Analysis (BEA) uses in the Regional Economic Accounts. In this framework, there are 3,138 county equivalent geographical territories in the United States. We exclude 32 counties for which information on rural population shares, one of our analysis variables, is not available from the Census Bureau. We also exclude 83 counties that we could not link with the IRS Statistics of Income (SOI) data. Our final analytic sample consists of a balanced panel of 3,023 counties that we follow from 2001 to 2017. Overall, 28 states expanded in 2014, 3 in 2015, and 2 in 2016. A total of 1,227 of these 3,023 counties are located in states that implemented the ACA Medicaid expansions in 2014. Another 174 counties belong to states that expanded in 2015, and 120 counties are in states that expanded in 2016. The remaining 1,518 counties have not yet adopted the ACA Medicaid expansions as of the end of our study period.

4.1 Regional Economic Information System

The primary outcome variable we use in the analysis comes from the Regional Economic Information System (REIS), which is a branch of the national income accounting system that was originally developed in the mid-1930s. Early versions of the income accounting system tracked personal income payments to individuals, including labor income, entrepreneurial withdrawals, dividends, interest, rents, and royalties. In 1966, the BEA began tracking the share of personal income from public assistance medical care benefit programs. In the 1970s, BEA developed estimates of personal income at the county level, including estimates of total federal Medicaid-CHIP (where CHIP is the children's health insurance program, providing healthcare to eligible children), as well as other programs, and transfers received by residents in each county. These figures represent federal transfer inflows attributed to each county, forming a key component of the resources available within local fiscal systems.

The county estimates provided on Medicaid transfers provided by BEA account for both fee-for-service (FFS) and managed care delivery of Medicaid. For the most part, the county-level Medicaid-CHIP transfer estimates are based on data from the Centers for Medicaid and Medicare Services (CMS). However, the BEA cautions that in some years and states, REIS estimates of federal Medicaid-CHIP transfers received in a county are imputed when county-level CMS data are not available, with this last available year varying across states.[6] For states in which county-level data were never available, the REIS uses recorded county distributions of federal spending on Temporary Assistance for Needy Families (TANF) to distribute state Medicaid totals into counties. Given the lack of availability of county-level source data, these estimates represent an approximation of the county-level distribution of medical care benefits as it relates to a county-level personal income concept, as opposed to a direct measurement of these payments.[7] Although imputation poses a potential concern, we believe that the REIS estimates are the best available data on the federal government transfers in terms of spending in each county through the Medicaid program.[8]

[6] The BEA does not provide a comprehensive list of states and time periods for which it was able to collect county-level Medicaid payments data. Such a list varies over time. BEA carries out internal validation studies on its imputation techniques, but does not grant public access to those studies.

[7] These details on the source and quality of the data have been provided to us via email correspondence with Lisa Ninomiya and Mauricio Ortiz at BEA between March and September 2020.

[8] The Census Bureau's Annual Survey of State and Local Government Finances does not provide infor-

The main outcome in our study is federal Medicaid-CHIP transfers per capita measured annually at the county level from 2001 to 2017. We construct the outcome by dividing total Medicaid-CHIP transfers by the county's population in that year, as measured by the Census Bureau.

4.2 Small Area Health Insurance Estimates

Our analysis is built around the idea that the increase in federal Medicaid transfers created by the ACA will largely depend on how many people in the county become eligible for Medicaid under the expansion. There is no perfect measure of the size of the newly eligible population in each county, and it is possible that the expansion itself may alter the size of the eligible population through crowd-out mechanisms (e.g., as suggested by Gallen and Mulligan (2018)). To avoid these problems, rather than use data on the number of individuals who actually receive or are eligible for new ACA Medicaid, we focus on a proxy measure of the pre-ACA size of the newly eligible population. Specifically, we use data from the Census Bureau's Small Area Health Insurance Estimates (SAHIE) program to estimate the number of uninsured non-elderly adults (ages 18 to 64) with income below 138% of the federal poverty line who were living in each county in 2010. We view these 2010 estimates as a *baseline* number of newly eligible uninsured in each county before the ACA took effect. This represents an estimate that is not confounded by the effects of the reform. We divide the county's baseline newly eligible population by the total population of the county in 2010 to obtain our proxy measure of the county's 2010 baseline newly eligible population share. It is important to remember throughout the paper that this is indeed a proxy measure, rather than the accurate number of newly eligible individuals.

We wish to discuss two possible weaknesses of our measure of individuals newly eligible to Medicaid. First, this proxy of newly eligible uninsured deducts the number of

mation on Medicaid financing for all counties in recent years.

non-elderly people not insured. By counting anyone who was eligible for Medicaid post-ACA but not insured, the variable is likely to overestimate the number of newly eligible and underestimate the per capita transfer estimates. This might involve two biases. On the one hand, there might be a systematic overcount of newly eligible individuals across states that is correlated with the state decision to expand Medicaid. On the contrary, a bias affecting the measure in the opposite direction is that the measure excludes individuals above 138% of the poverty line on Medicaid.

Second, each state somewhat differed in the eligibility rules, such that not all uninsured under 138% of the federal poverty lines became newly eligible. Further, pre-ACA (i.e., the period we use to build our newly eligible share measure), the states had different definitions of income for determining eligibility. The ACA then introduced a uniform definition and imposed the modified AGI to be the income measure to consider for eligibility.

4.3 Navigator Funding, Medicaid Fee Ratios, Statistics on Income

Eligible population shares are, we posit, the main factor that determines the fiscal effects of Medicaid expansion in each county. However, other factors that affect take-up or Medicaid costs may also influence transfer size. Such factors include ACA-related marketing, outreach, and enrollment assistance. The ACA included funding for "navigators" to help people obtain health insurance through the ACA insurance exchanges; outreach efforts have varied across geographic areas and may have also affected take-up of Medicaid benefits. To examine this possibility, we use data on Navigator funding awards in 34 states for the year 2016, assembled by the Kaiser Family Foundation based on CMS data.[9] We compute a per capita measure using 2016 population data, so that it is comparable to the

[9] We have nagivator rates for the following states: Alabama, Alaska, Arizona, Delaware, Florida, Georgia, Hawaii, Illinois, Indiana, Iowa, Kansas, Louisiana, Maine, Michigan, Mississippi, Missouri, Montana, Nebraska, New Hampshire, New Jersey, North Carolina, North Dakota, Ohio, Oklahoma, Pennsylvania, South Carolina, South Dakota, Tennessee, Texas, Utah, Virginia, West Virginia, Wisconsin, and Wyoming.

outcome variable of Medicaid transfers.

Medicaid reimbursement rates vary substantially across the country, and higher rates will translate into larger transfers from the ACA Medicaid expansion, all else equal. The ACA actually required states to increase Medicaid reimbursement rates to match Medicare reimbursement rates for selected primary care services in 2013 and 2014, with the federal government paying fully for the "fee bump." Many states chose to continue with these higher rates even after the two-year period of extra federal funding ended (Zuckerman et al., 2017).[10] The enhanced fee schedule suggests that the ACA expansions may have larger effects on federal transfers in states that initially had lower Medicaid reimbursement rates. To explore this possibility, we use data on Medicaid-to-Medicare fee ratios from the Urban Institute's Medicaid Physician Survey to measure the relative generosity of each state's Medicaid program (Zuckerman et al., 2017).[11] The Medicaid-Medicare fee ratio is the average ratio of Medicaid and Medicare reimbursement rates for the same service under the two different programs. In our analysis, we build a variable for the average of the 2008 and 2012 Medicaid-to-Medicare fee ratios for each state using information reported in Zuckerman et al. (2009) and Zuckerman (2012).

To assess the progressiveness of the ACA expansion's effect on federal transfer spending, we use the Internal Revenue Service's Statistics of Income (SOI) data on the total income tax paid[12] by people living in each county in 2010 and the county-level AGI. On the one hand, the income tax is the data source used in assessing federal tax contribution in prior literature on health spending and taxing distribution (Holahan and Haley, 2020). On the other hand, we believe that, to stick to the traditional definition of progressivity, the consideration of an income measure, rather than taxes paid, is warranted. Hence,

[10]Decker (2018) studies the effect of the primary care fee increase on physician participation in the Medicaid program and finds no association between the size of the fee increase in a state and the fraction of physicians who accept Medicaid patients, possibly due to its temporary nature.

[11]We use fee ratio rather than other determinants of local area variation in spending, such as the Dartmouth Atlas measures (Skinner, 2011), because Medicaid reimbursement is typically far below reimbursement from other sources.

[12]This SOI income tax variable is based primarily on line 55 of form 1040 plus information from forms 1040A and 1040EZ when they are filed.

we also adopt AGI in our analysis on progressivity. We investigate how these two SOI county-level variables, total income tax and AGI, correlate with our estimation of federal transfers triggered by the ACA and received by the county's residents.

5 Methods

We use m_{cst} to represent Medicaid-CHIP transfers per capita in county c and state s during year t. E_c is the number of uninsured nonelderly adults with income less than 138% of the poverty line in 2010, expressed as a fraction of the county's 2010 population. This is our proxy measure of the baseline (pre-ACA) share of the county's population that would become newly eligible for Medicaid if the state adopted the ACA expansions. Let $ACA_{st} = 1$ if state s has adopted the ACA Medicaid expansion as of year t. $ACA_{st} = 0$ in all years for all non-expansion states. We fit two-way fixed effects regression models with interaction terms to model the heterogeneity in the effect of the ACA expansion on federal Medicaid transfers at the county level. In the simplest specification, the size of the expansion effect varies linearly in the baseline size of the newly eligible population in the county:

$$m_{cst} = \alpha ACA_{st} + \beta(ACA_{st} \times E_c) + a_c + b_t + \epsilon_{cst} \tag{1}$$

In the model, a_c and b_t are county and time period fixed effects. The effect of the ACA expansion on federal Medicaid-CHIP transfers is $\Delta_c = \alpha + \beta E_c$, where α is represents the transfer effect in a county with no newly eligible adults as of 2010, and β measures how the size of the transfer effect changes with the newly eligible population share. We expect $\beta > 0$ because the expansion will induce a bigger enrollment change in places with larger populations of newly eligible people, and because the size of the federal transfer is primarily determined by new enrollment. We also examine models where the treatment effect is allowed to vary according to three more flexible specifications: a quadratic function in the newly eligible share, a linear spline with a knot at the median of the newly eligible share, and a model with indicator variables for the quintile categories of the newly eligible share. In supplementary analysis, we augment the basic model to allow the county-specific expansion effect to depend on both state-level ACA navigator funding and the Medicaid-to-Medicare fee ratio using:

$$
\begin{aligned}
m_{cst} = \alpha ACA_{st} + \gamma Navigator_{st} + \theta MedicaidMedicareFee_{st} + \lambda(ACA_{st} \times Navigator_{st}) \\
+\pi(ACA_{st} \times MedicaidMedicareFee_{st}) + \beta(ACA_{st} \times E_c) + a_c + b_t + \epsilon_{cst}
\end{aligned}
$$

We augment this linear model with more flexible (quadratic, spline, quantile indicator) specifications as well. There are three main identifying assumptions in the analysis. We assume that federal Medicaid transfers per capita would have followed a common trend across all counties in the absence of the ACA expansions, and that unobserved determinants of federal Medicaid transfers are strictly exogenous with respect to the history of the ACA expansions, ruling out differential pre-trends or anticipatory effects. Finally, our strategy assumes that treatment effect heterogenity across counties is determined by a observed baseline measures of newly eligible population shares with a specific functional form. (The supplementary analysis allows effects to depend on state level navigator funding and fee ratios as well.)

We examine sensitivity to the functional form restriction by estimating models with more flexible specifications. We assess the plausibility of the common trend and strict exogeneity assumption by fitting event study regressions that trace changes in Medicaid transfers in the years preceding and following each state's expansion implementation. Specifically, we let Y_s be the year in which state s expands Medicaid under the ACA. Then, $YSA_{st} = t - Y_s$ measures the number of years between the current period and the year of adoption in a given state. For example, $YSA_{st} = -2$ when state s is observed 2 years before its ACA expansion and $YSA_{st} = 2$ when the state is observed 2 years after the ACA expansion. Let $D(j)_{st} = 1(YSA_{st} = j)$ be a dummy variable set to 1 when YSA_{st} is equal to j. Our event study is a regression of county-level federal Medicaid transfers per capita on dummy variables for each level of YSA_{st}:

$$m_{cst} = \sum_{j=-7}^{-2} [\beta_j D(j)_{st} + \alpha_j (D(j)_{st} \times E_c)] + \sum_{h=0}^{3} [\theta_h D(h)_{st} + \delta_h (D(h)_{st} \times E_c)] + a_c + b_t + \epsilon_{cst}$$

In the model, the β_j and α_j coefficients measure the response of the outcome variable to future policy changes, and whether that anticipation effect varies with the county's pre-ACA newly eligible population share. Under the strict exogeneity assumption, future events do not affect current outcomes, so we expect all these coefficients to be equal to zero. The θ_h and δ_h coefficients measure the effects of the policy variable during each post-adoption period, and how that effect varies across counties with different pre-ACA newly eligible population shares. If the effect of the policy is immediate and does not change over time, then all the θ_h and δ_h coefficients will be the same. However, if the effect of the policy grows or shrinks over time, these coefficients will provide a measure of the program's time-varying effect.

6 Results

Table I reports the pre-ACA 2010 means and medians of each of the variables used in our analysis for non-expansion and expansion states. Note that we show and use the values for 2010, a pre-ACA year, so that they represent baseline measures before the reform. Table II shows the means and medians of the Medicaid-to-Medicare Fee Ratio and Navigator Funding variables that we incorporate in the second part of the paper. These variables are only available at the state level.

Although the analysis in this work is at the per-capita level, in Table I we show total numbers for both population and spending. We use these to obtain our per-capita estimates or population shares throughout the paper. It is clear from the table that expansion counties have larger populations than non-expansion counties. For instance, in 2010, the population of the median expansion county was 27,729. In comparison, the median non-expansion county had a population of 23,411 people. As a consequence, total Medicaid (and Medicare) transfers are much higher in the expansion counties. However, pre-ACA transfers per capita are more comparable. In both expansion and non-expansion states, the median county received $1,235 per capita in federal Medicaid transfers in 2010, with the median counties in expansion states receiving about $20 more than those in non-expansion states.

The 2010 newly eligible population share varies substantially across the country. In expansion counties, uninsured non-elderly adults with income below 138% of the federal poverty line represented about 5% of the population in 2010. In contrast, the mean 2010 newly eligible population share was 7% in non-expansion counties. Figure II shows a map of the United States with counties shaded according to their 2010 newly eligible population shares. The darkest shading applies to counties where uninsured non-elderly adults with income less than 138% of the federal poverty line make up 0.7% to 17% of the population. The lightest shading goes to counties where the newly eligible population share is less than 3.4%. The newly eligible population share is particularly high in the West South-Central and West Mountain regions of the United States. In contrast, newly eligible population shares are lower in the Midwest and New England. The wide range of color shades indicates that there are stark differences across the country in the share of the population that would benefit from ACA Medicaid expansion. If we consider the share of newly eligible individuals to be a proxy for new enrollments triggered by the ACA, then the heterogeneity in the newly eligible population share means that there will be geographical variation in the number of new enrollees induced by the ACA. This type of variation has already been used in the ACA literature in "dose-response" approaches to show that areas with higher uninsurance pre-ACA benefited more from insurance coverage under the ACA (Courtemanche et al., 2017). Similarly, the fact that counties in non-expansion states have higher mean and median newly eligibility rates in the population suggests that these counties would likely receive a relatively large increase in federal transfers per capita if their states were to adopt the expansion.

6.1 Assessing The Common Trends Assumption

Figure III shows per capita Medicaid transfers to county populations in non-expansion states, and in states that expanded in 2014, 2015, and 2016. Overall, the level of transfers in the three groups of counties moves together and is approximately parallel up until the expansion years, which are indicated by three vertical bars (2014, 2015, or 2016). Figure III suggests that the parallel trends assumption underlying our main analysis is reasonable in our data.

To investigate the possibility that differential pre-trends might lead to a bias in our main difference-in-differences specifications, we fit event study models that let the gap between expansion and non-expansion states vary in the years before and after the actual policy change. The coefficients on the policy lead and lag variables from the event study regressions are plotted in Figure IV. The coefficients on the pre-ACA expansion variables are small in magnitude, negative, though trending upward towards zero, and statistically significant. Despite the presence of some minor pre-trends, these are slight relative to the large increases in transfers that occur after the ACA expansion. The coefficients on the post-expansion terms are large and statistically different from zero. The post-period effects grow with time since adoption, dramatically so in the first and second post-adoption years.

The pattern of coefficients in Figure IV broadly supports our difference-in-differences research design, although there is some evidence that, in the period leading up to the expansions, Medicaid enrollment may have been growing slightly faster in expansion states than in non-expansion states. The results also suggest that the size of the expansion effect on federal transfers grew with time since implementation, especially in the two years, which makes sense if people take some time to learn about and enroll for the new benefits.

Because the event study shows some negative and statistically significant pre-trends, the treatment effects we estimated might be exaggerated. To check for the robustness of these results, we implemented a comparative interrupted time-series model as a robustness check. The result, in the Appendix, overall supports the above conclusions.

6.2 Difference-in-Differences Models

Table III reports estimated coefficients from four models of the effects of the ACA Medicaid expansions on federal Medicaid-CHIP transfers per capita. Each specification allows for a different degree of flexibility in how the newly eligible population share enters the model. All models are based on county-level data from 2001 to 2017, and they include county fixed effects, year fixed effects, and a binary variable set to one when the state adopts the ACA Medicaid expansion. The first model in Table III has an interaction term between the ACA expansion variable and the pre-expansion newly eligible population share. In the second model, we interact the ACA expansion variable with a quadratic function of the newly eligible population share. The third model is a spline specification, which allows the eligible population share to be piecewise linear above and below a knot at the median newly eligible population share. Finally, in the fourth model, we include dummy variables for five quintile categories of the newly eligible population share.

All four models provide evidence that the ACA expansion led to much larger increases in federal Medicaid transfers per capita in counties where the newly eligible population share was larger. There is some evidence in the quantile model (column 4) that the relationship between Medicaid transfers and the newly eligible population share is not linear; however, neither the coefficients on the square of the newly eligible population in the quadratic model nor on the spline term in the spline model are statistically significant. Figure V plots the implied effect of the expansion on per capita Medicaid transfers as a function of the newly eligible population share from each of the four models. It also shows the density of the newly eligible population share across counties. The four models agree almost perfectly for counties where the newly eligible population share is between 2% and 8%. This is where most of the observations are concentrated, thus maximizing the estimates' precision.

We use the coefficients from the models to estimate the effect of the expansion on the transfer received by each county. Table IV shows selected averages of the county-specific effects from each of the four models. The average treatment effect on the treated (ATT) counties gives the average effect across the subset of counties located in expansion states. The ATT estimates represent the expansion effect on federal Medicaid transfers that have actually been experienced by the counties in expansion states relative to a counterfactual scenario of no Medicaid expansion. The results imply that the ACA Medicaid expansions increased federal Medicaid transfers by about $361 per capita in the average county within expansion states (i.e., ATT).

We combine the coefficient estimates with the baseline newly eligible population share in non-expansion counties to form the implied expansion effect in each of these counties. The average treatment effect on the not treated (ATNT) counties gives the average effect across all of the counties in non-expansion states, turning "on" the expansion variable. Our ATNT estimates imply that if the non-expansion states had adopted the expansion, federal Medicaid transfers would have increased by about $554 per capita for those counties on average. These forecasts imply that the expansion would lead to much larger increases in federal transfers in non-expansion states than in expansion states.

The average treatment effect (ATE) represents the average effect across all counties in both expansion and non-expansion states. At $456 per capita, it (unsurprisingly) lies between the ATT and ATNT estimates. The results make sense given that the treatment effect heterogeneity in our model stems from the (proxy) newly eligible population in each county. Since the non-expansion counties have, on average, larger newly eligible population shares, a hypothetical Medicaid expansion would trigger more enrollment per capita and more federal spending per capita. Table IV also shows that, on average, the effects are essentially the same across the four model specifications.

Figure VI shows a map of the county-specific expansion effect estimates in ACA expansion states. Counties with the largest ACA-induced increases in federal Medicaid transfers per capita are shown in the darkest shading. Areas with the largest expansions in federal transfers are in Alaska, the West Mountain region, and the West Pacific region. Medicaid expansion led to lower average Medicaid transfers in New England, the Middle Atlantic, and the Midwest. Figure VII shows the forecasted expansion effects in counties located in non-expansion states. As expected, this map is much darker than the one for counties in expansion states. Based on the average Medicaid federal transfers its county residents would receive, the West South-Central region appears to be the largest potential beneficiary of the expansion. The results imply that for Mississippi, the state with the highest average share of county-level newly eligible individuals in 2010 (i.e., 0.084), adopting the ACA Medicaid expansions would increase federal transfer spending on the Medicaid program by about \$806 per capita. In the average county in Georgia, where the uninsurance rate in 2010 was 7.9%, the expansions would increase federal spending on the Medicaid program by \$740, and in Texas counties, where the uninsurance rate was 7.8%, spending would increase by \$724. These findings are relevant to the fiscal federalism literature on the determinants of local use of federal spending. In particular, Carlino et al. (2021) shows that local spending trends are highly dependent on state partisanship, with the marginal benefit to spend of republican governors being much lower. Not only might this explain the expansion choices made by the states, but also a governor's partisanship could determine geographical differences in transfer sizes.

6.3 Take Up and Cost Factors

The basic model discussed so far allows the fiscal effects of the ACA expansions to vary by the anticipated share of the county population that will become newly eligible for Medicaid. However, the effects of the expansion may also vary across locations because of state-level differences in the cost structure of the Medicaid program and because of state-level differences in outreach effort. To examine the role of cost structure and take-up related factors, we estimated more elaborate regression specifications with additional terms that interact with the ACA expansion dummy variable. For explanatory purposes, we wrote the linear version of this model in Section 5. We used state-level Navigator funding as a proxy for outreach efforts in the state. Navigator spending might increase take-up of the program by reducing the administrative burden of learning about and signing up for it. We use the Medicaid-Medicare fee ratio as a proxy measure of the generosity of reimbursement in each state. Table V reports results from expanded DID models that incorporate these additional state-level factors in both parsimonious and flexible ways. The sample size for these extended models is smaller than the sample size used in our main analysis because the Medicaid-Medicare fee ratio is not available for Tennessee, and the Navigator spending is missing for 17 states. [13] The results are qualitatively similar in the expanded models, but the magnitudes and precision are somewhat different. Even after we add the state-level covariates and limit the sample, the effect of the expansion on transfers increases with the population share of newly eligible individuals at baseline. The state-level factors (Navigator spending and Medicaid-Medicare fee ratios) do not appear to be a major driver of heterogeneity in the fiscal effects of the expansions across counties. In the most parsimonious specification with only linear interaction terms, the effect of the expansions is increasing in the state's Navigator expenditures per capita,

[13] The Navigator spending variable is missing for one non-expansion state: Idaho. It is also missing for 16 expansion states: Arkansas, California, Colorado, Connecticut, District of Columbia, Idaho, Kentucky, Maryland, Massachusetts, Minnesota, Nevada, New Mexico, New York, Oregon, Rhode Island, Vermont, Washington.

suggesting that outreach efforts did lead to higher take-up and larger federal Medicaid transfers. However, the effects are noisier and not statistically significant in the more complicated models that allow the effect of Navigator spending to alter the expansion effect non-linearly. We find little evidence that the size of the effect of the expansions on federal transfers is affected by state Medicaid-to-Medicare fee ratios, suggesting that differences in state Medicaid costs are not a major driver of federal Medicaid expenditures.

In Table VI, we show average treatment effects from the more elaborate models. The ATE across all counties, in expansion and non-expansion states, is $349 per capita. The ATT implies that across counties in states that have actually expanded their Medicaid program, federal Medicaid transfers grew by about $208. When we average only across counties in non-expansion states, the average per capita impact of the ACA on Medicaid transfers increases to $441. The results are quite similar across the different specifications, but they are often substantially smaller than they were in our original models, which allowed the effects to only depend on the newly eligible population share. Ex ante, the smaller average effects could have been due to the impacts captured by the state-level factors or by the change in the composition of counties in the sample. To investigate, we re-estimated the simpler model without the state-level factors, but limited the sample to the counties included in the expanded models. The average treatment effects from the simple model in the limited sample are shown in the Appendix tables X and XI. The results are nearly identical to the specifications that include the state-level factors, implying that the differences in the average effects are mainly an artefact of the sample construction and do not indicate an important role for the state-level factors.

6.4 Who Pays For The Transfers?

The ACA Medicaid expansions are intended to be financed mainly from income taxes and cost reductions in the Medicare program. To clarify the way in which ACA-induced changes in the geography of federal transfer spending are related to these sources of funding, we plot expansion effects for a county against its baseline federal income tax contributions from the SOI data. Figure IX shows scatterplots of ACA expansion effects against the per capita income tax revenue paid in a county in 2010[14]. In both the expansion and non-expansion data, the size of the ACA-induced increase in federal Medicaid transfers falls as the average income tax paid by a county increases. In other words, the counties that benefit the most from the ACA in terms of increased federal transfers are also the counties that pay the least in federal income taxes per capita. This is descriptive evidence that the ACA expansion was indeed progressive and redistributed resources from high-income individuals in the form of income taxes to lower-income individuals in the form of per capita Medicaid transfers. Our findings are consistent with earlier research at the state level that demonstrates progressivity in the financing of Medicaid (Holahan and Haley, 2020).

In simple regressions of the natural logarithm of county transfer effects on the natural logarithm of county 2010 income tax contributions[15], we find that Medicaid transfers fall by about 0.86 per cent for each 1 per cent increase in tax dollars. In counties in expansion states, a 1 per cent increase in tax dollars is associated with a 1.07 per cent decrease in average ACA transfer to the county. When only considering counties in non-expansion states, instead, a 1 per cent increase in tax dollars leads to a 0.52% decrease in the average dollar ACA transfers to the counties.

To check whether there is any relationship between Medicare cost savings that have occurred under the ACA (one of the intended revenue sources for the Medicaid insurance expansion) and the size of the ACA Medicaid expansion transfers, we compare county-level per capita Medicaid expansion transfers with the long difference in per capita Medicare transfers to that county between 2010 and 2017. In essence, these graphs ask whether there is any connection between areas that experienced the lowest increases in Medicare

[14]We obtain a per capita measure of county-level income tax by dividing the 2010 county's total income taxes by the county's population

[15]Before transforming to the natural logarithm of transfers, we dropped the negative values, if any. As a result, our sample decreased by 567 counties for which the average transfer's prediction is negative.

costs and the size of the ACA Medicaid expansion. Unlike the strong association with income taxes in Figure IX, the scatterplots in Figure X suggest that there is a very slight negative connection between the Medicaid expansion effects and Medicare cost reductions. This is not necessarily surprising; there was no expectation that the financing of the Medicaid expansion by the reductions in Medicare cost savings would occur within-county, but this is an interesting new result on which no prior evidence exists.

Finally, to investigate more directly the progressivity of the expansion, we check how our county-level per capita estimate for the transfer post-expansion is correlated with the county-level per capita AGI[16]. The relationship is in Figure XI. On the left panel, we plot counties in expansion states, and on the right panel, we show the results for counties in non-expansion states. To improve the visibility of the scatterplots, in the plotting of the scatter, we drop all counties with an average per-capita AGI of above 100,000 dollars, but keep them for the production of the linear fit. The figure shows a clear negative relationship between per capita AGI and our estimated per capita transfer effect: counties at lower levels of AGI receive the highest transfers, hence supporting evidence that the Medicaid expansion was indeed a progressive measure. Also, we run a similar log-log regression like we did for the income tax variable[17]. There is a strong negative relationship between county-level per capita AGI and county-level per capita ACA federal transfers. The coefficient on the log of AGI implies that one per cent more of county-level per capita AGI corresponds to about 1.40 per cent less of ACA Medicaid transfer effects to that county, with that percentage being 1.84 for counties in expansion states and down to 0.82 per cent for counties in non-expansion states.

[16]We obtain a per capita measure of county-level AGI by dividing 2010 total county's AGI by the county's population

[17]Before we run the regression of log ACA per capita county-level transfers on county-level per capita AGI, we drop counties for which the AGI value was negative

6.5 Enrollment Effects

Research on the substate effects of the ACA expansions on Medicaid enrollment is limited because there is no publicly available dataset of Medicaid enrollment at the county level. The only work we are aware of on this topic is by Barker et al. (2017), who collected county-level Medicaid enrollment administrative data directly from 40 states in December 2012 and December 2015. They compare the growth in total Medicaid enrollment between these two periods and find much higher growth in counties located in expansion states and some evidence that growth was higher in metropolitan areas than in rural and micropolitan areas. However, to date, no study has estimated the heterogeneous effects of ACA Medicaid expansions on county-level Medicaid enrollment.

To help fill this gap in the literature, we use our estimates of the fiscal effects of the ACA expansions to form "back of the envelope" estimates of the number of people who enroll in Medicaid because of the expansions in each county. Our approach is premised on the idea that the federal transfers to a county are proportional to the number of people who are actually induced to enroll. In essence, we simply need a method of re-scaling our estimates from "dollars of transfers per capita" to "new Medicaid enrollees," which we can do using information on the cost of a new enrollee resulting from the expansion. To demonstrate this idea, use N_c to represent the population of county c. Δ_c is our DID estimate of the effect of ACA expansion on federal transfers per capita in county c. Then let AC represent average federal expenditures per "expansion adult." A crude estimate of the number of new Medicaid enrollees in county c is $NE_c = \frac{\Delta_c \times N_c}{AC}$, that is the total amount of dollars flowing to a county as a result of the expansion (i.e., $\Delta_c \times N_c$), divided by the average cost of a new enrollee generated by the expansion (i.e., AC).

The main unknown quantity is AC, the average federal expenditure per expansion adult. We obtained the nationwide average estimate of AC from the 2018 Actuarial Report on the Financial Outlook for Medicaid, which reports that the federal government spent about $\$5,669$ per "expansion adult" in 2017, for a total expenditure of about \$69 billion on expansion adults across the country (Truffer et al., 2018).[18] Using the national-level average AC estimate in the formula above, we estimate the number of people who were induced to enroll in the Medicaid program because of the expansion for each expansion county, and we also forecast the number of people who would enroll in each non-expansion county if their state implemented the expansions.

To check the performance of our method, we compute the total enrollment implied by our county-level estimates for each expansion state and compare our aggregate forecasts with publicly reported data on actual enrollment in each *state*. In Figure XII, the vertical axis shows reported enrollment from the CMS, and the horizontal axis shows the statewide total of our county-level back-of-the-envelope estimates, which we obtained by applying the CMS national-level average cost (i.e., 5,669). Most of the states fall very close to the 45-degree line in the graph, suggesting that our state-level totals from the county-level estimates are a good approximation of the administrative data. The correlation between the two measures is 0.973. The fact that our re-scaled county-level transfer effects are able to replicate state-level total enrollment figures relatively closely gives us some confidence in our overall approach and in the credibility of the county-level enrollment estimates.

Table VII summarizes the disaggregated county-level enrollment estimates from each of the four underlying treatment effect models we use in our main analysis.[19]. This analysis estimates the predicted number of new enrolled individuals at the county level for all counties, for counties in expansion states, and for those in non-expansion states. To do this, we have rescaled our estimates by two quantities: a measure of average cost for each new enrollee, and a measure of county-level population.[20]

[18] County-level information on the average cost would allow us to estimate more precise local enrollment numbers. However, to our knowledge, such data is not available.

[19] As before, the results vary only slightly across the specifications.

7 Conclusion

In this paper, we investigate how the ACA expansion alters federal Medicaid transfers at the county level. The Medicaid program, in general, is financed jointly by the federal and state governments. However, nearly 100% (specifically, 100% in the first three years, and 90% thereafter) of the ACA Medicaid expansion was funded at the federal level, especially during our study period. Federal shares of benefits provided through Medicaid are reimbursed as transfers to states (which spend directly or through Medicaid managed care entities) and are recorded/estimated at a disaggregated (county) level by the Bureau of Economic Analysis based on where beneficiaries live. This measure of Medicaid transfers at the county level has not previously been studied in the literature on the ACA. We examine the effect of Medicaid expansion on the amount of Medicaid transfers that flow to each county, allowing the effect to vary in proportion to the county-level baseline share of people who are likely to meet the expanded eligibility criteria and other factors that may affect program take-up rates or the costs of running the program. Our work complements the existing literature on the state-level budget implications of ACA Medicaid expansions, e.g., Bachrach et al. (2016); Gruber and Sommers (2020), which considers many perspectives relevant for states, such as cost savings from uncompensated care costs and taxes levied by the state on healthcare providers. In contrast, our analysis focuses solely on the flow of federal reimbursements for program spending on behalf of beneficiaries in each county. Examining how federal benefits from new social programs flow to different parts of the country is important for long-standing questions in public finance, as well as for informing contemporary policy decisions. So far, 10 states have chosen not to expand Medicaid, and decisions about the ACA and Medicaid coverage have been at the forefront of political debate to this very day.

We add five contributions to the literature. First, we find that the ACA expansions increased federal Medicaid transfers by about \$361 per capita for the average county in an expansion state. However, the standard deviation of the increase was about \$247. This implies that there is substantial heterogeneity in the fiscal consequences of expansion among counties in the expansion states. Second, we estimate how much additional federal funding would have flowed to counties in non-expansion states had they expanded, and find that amount to be about $554 per capita on average (standard deviation $240). These results imply that ACA Medicaid expansions would have led to much larger increases in transfers per capita in non-expansion states than in expansion states, because non-expansion counties have a high prevalence of low-income uninsured individuals who would become eligible for Medicaid under the expanded criteria.

Third, we find that the transfer effects of the ACA directed larger per-capita transfers toward lower-income counties. Counties that paid more in federal income taxes per capita in 2010 and those with higher AGI in 2010 received much smaller increases in transfers per capita. This provides one framework for considering how the ACA functions as a redistribution mechanism from high- to low-income counties in the form of Medicaid transfers. These findings are consistent with the explicit means-tested nature of Medicaid benefits, and contrast with the Medicare program, where there is less certainty about the degree of redistribution (Bhattacharya and Lakdawalla, 2006; McClellan and Skinner, 2006; Rettenmaier, 2012; Niu, 2017). Our results complement other strands of economics research on the distribution of *lifetime* Medicaid transfers, such as De Nardi et al. (2016), which relates to the optimal size of the Medicaid program. In the spirit of Musgrave (1959), the ACA Medicaid expansion is a redistributive program occurring almost fully at the central (federal) level, traditionally preferred to redistribution conducted by smaller levels of government. Thus, our evidence characterizing redistribution in this latest of Medicaid expansions through the ACA is relevant for discussions of Medicaid financing formulas (Clemens and Ippolito, 2018). These findings reinforce conclusions by Gaubert et al. (2021) that geographically oriented federal transfers push back against widening economic imbalance across local areas in the U.S.

Fourth, we provide the first test of whether the ACA's Medicare cost savings—one of the law's intended financing mechanisms—are geographically linked to Medicaid expansion gains. We find no within-county relationship between Medicaid transfer increases and Medicare transfer changes, suggesting that the ACA's financing structure does not create offsetting fiscal effects at the local level.

Fifth, we use our estimates of federal transfers at the county level to estimate the number of new enrollees as a result of the ACA Medicaid expansion. Although this is done through a simple transformation of our Medicaid transfer (dollars per capita for each county) estimates, we believe that the estimates are useful, as there are currently no publicly available measures of ACA-expansion-induced enrollment in Medicaid at the county level. This also shows the number of new enrollees who might gain Medicaid in non-expansion counties, were their states to adopt the expansion. This exercise produces estimates of who would be covered through Medicaid expansions in the remaining states through a process that is quite different than the micro-simulation models developed by the Urban Institute and RAND (Simpson, 2020; Cordova et al., 2013; Price and Eibner, 2013). Nevertheless, the conclusions reached by our analysis are in line with that work. For example, we estimate that, on average, 9% of the population of the average county would become newly enrolled in non-expansion states. For comparison, Simpson (2020) estimates that 6.8 percent more of the non-elderly population in non-expansion states would be insured by Medicaid (Simpson (2020), Table 1, row 5). Future work should consider the impacts of these spending differences on area-level outcomes that result from improved public infrastructure, above and beyond the impacts of individual eligibility for Medicaid, as done in the school finance literature that exploits the local area variation in distribution of resources from policy change (Jackson et al., 2016).

While our analysis has limitations, including data imputation in some states and the inability to separate newly eligible from welcome mat enrollees (discussed in Sections 4 and 5), our core findings on the redistributive pattern of ACA transfers are robust across specifications. These findings highlight Medicaid as a central, yet underexamined, instrument of fiscal federalism. Beyond its health role, the program reshaped county-level resource flows by channeling substantial federal dollars toward economically weaker jurisdictions. For public budgeting scholars and practitioners, these results underscore the importance of viewing large categorical grants as budgetary tools with implications for revenue composition and intergovernmental redistribution. Looking forward, understanding how programs like Medicaid direct resources across counties offers valuable insights for designing future federal aid—whether in health, infrastructure, or emergency relief—in ways that promote balanced and efficient allocation across all levels of government.

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8 Tables and Figures

Figure I: ACA Medicaid Expansion (State Level)

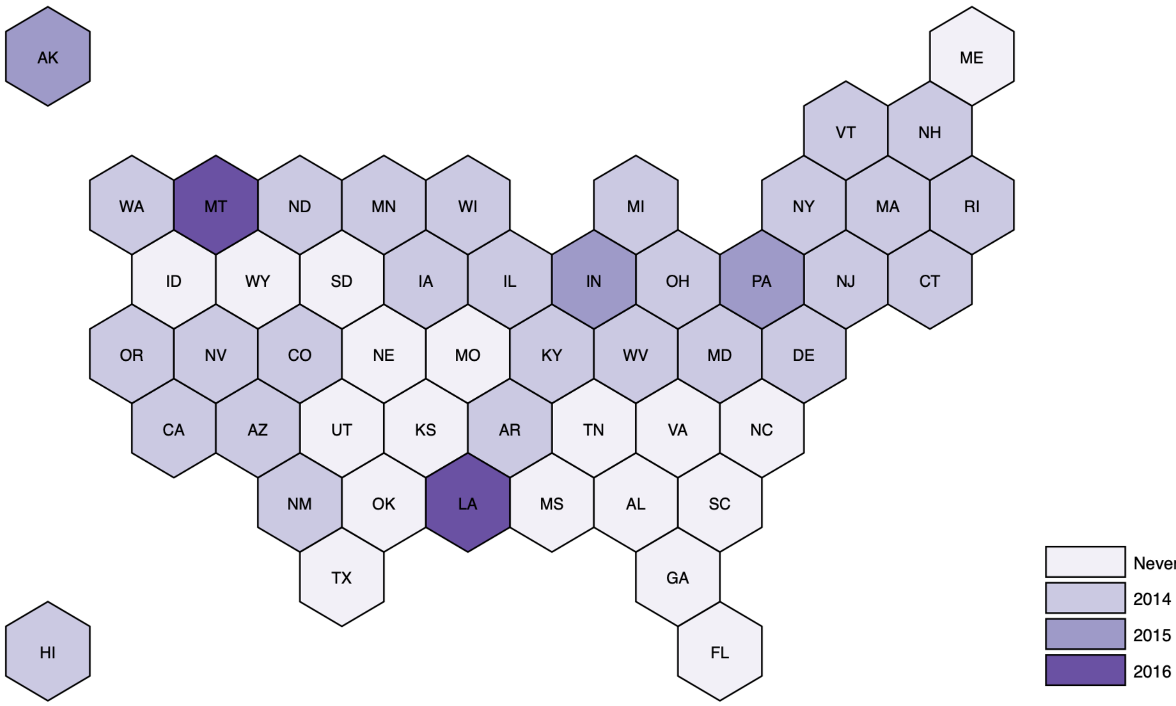


Table I: County Level Descriptive Statistics - 2010 Federal Transfers, Population & Percent Rural

	Never Expanded Mean	Median	Expanded Mean	Median
Medicaid	87,018	31,827	156,853	35,758
PC Medicaid	1,343	1,256	1,351	1,235
Population	81,446	23,411	108,855	27,729
Eligibility Rate	.069	.069	.05	.048
Medicare	138,778	46,710	179,048	52,282
PC Medicare	1,983	1,972	1,874	1,877
PC Income Tax	1,871	1,588	2,095	1,810
Per Cent Rural	61	63	58	58
Observations	1,034		1,989	

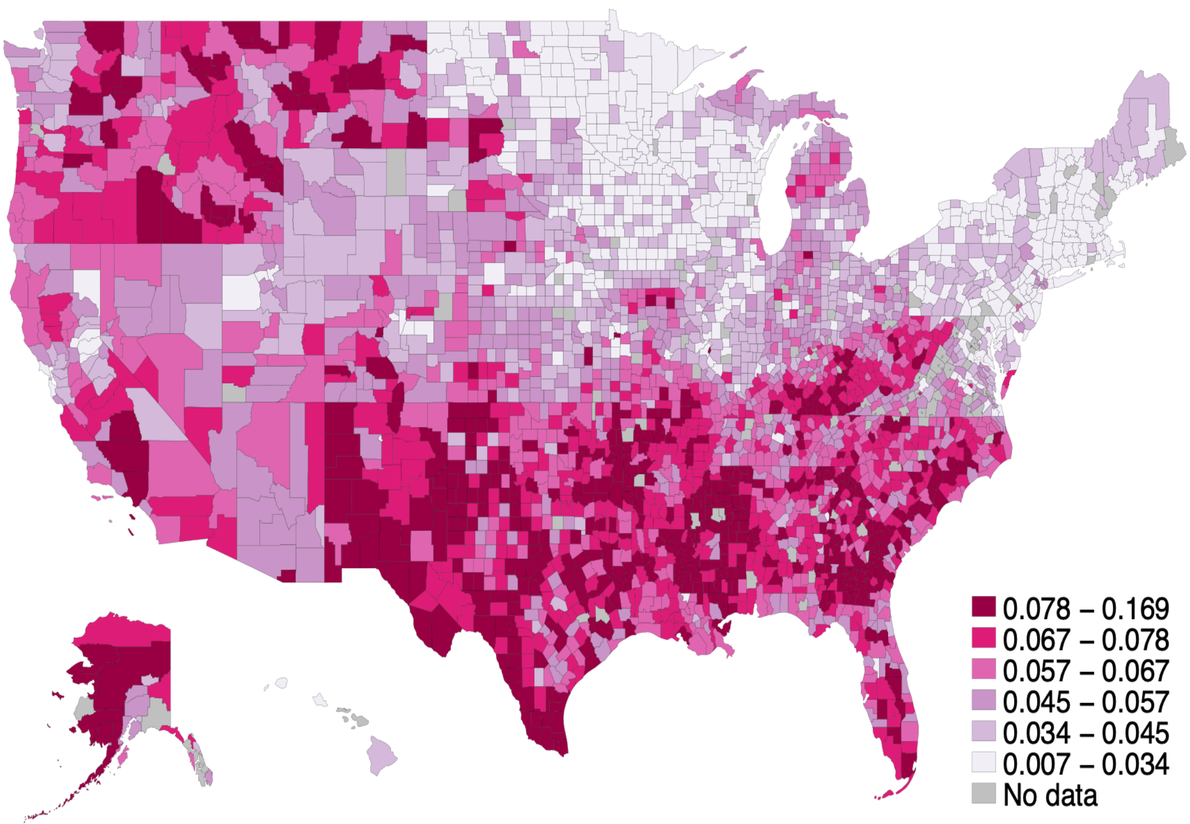
Note: Sample split by state expansion status as of 2021. Medicaid and Medicare rows are in dollars (in thousands of dollars for the totals). p/c stands for per capita. Eligibility Rate is the estimated county-level average share of adults who would gain eligibility for Medicaid as a result of the ACA, estimated from 2010 SAHIE data. Statistics in this table are unweighted. The full sample of federal transfers (REIS) contains 3,140 counties; 34 have missing data on federal transfers, federal transfers, or population in some years, and 83 lack SOI data, resulting in 3,023 counties for analysis (1,034 in non expansion states and 1,989 in expansion states).

Table II: State Level Cost and Take Up Factors

	Never Expanded Mean	Median	Expanded Mean	Median
Medicaid Medicare Fee Ratio 2008	.86	0.90	0.83	.86
Medicaid Medicare Fee Ratio 2012	.75	0.76	0.75	.76
PC Navigator Funding 2016	.018	0.02	0.01	.012

Note: Medicaid Medicare Fee ratio data are available for all but one state (Tennessee, a non-expansion state). The navigator spending variable is missing for 17 expansion states: Arkansas, California, Colorado, Connecticut, District Of Columbia, Idaho, Kentucky, Maryland, Massachusetts, Minnesota, Nevada, New Mexico, New York, Oregon, Rhode Island, Vermont, and Washington.

Figure II: Geographical Distribution of the Newly Eligible Population Share (County-level data)



This map shows the fraction of each county's 2010 non-disabled, non-elderly, and childless population with income up to the 138% of the Federal Poverty Line (Source: SAHIE).

Figure III: Parallel Trends Assumption

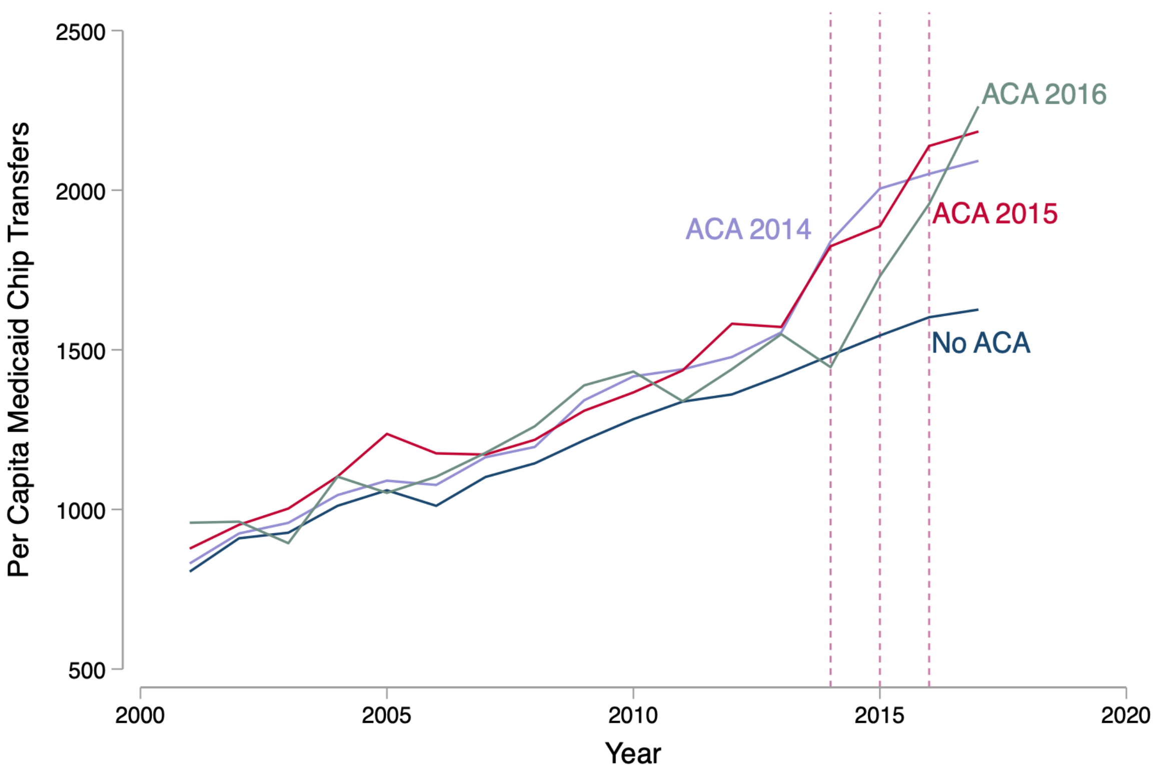
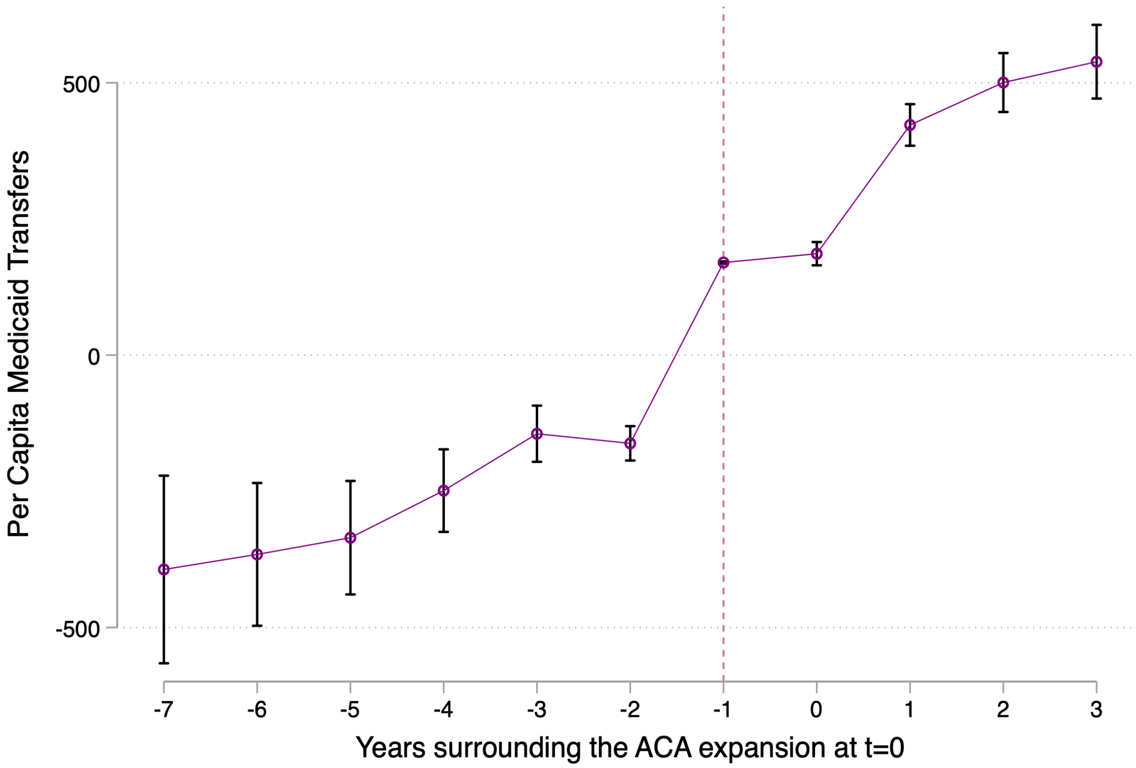


Figure IV: Event Study



Note: We plot the regression coefficients and corresponding confidence intervals obtained from the event study regressions. Each coefficient represents the average impact of the reform at any given pre-ACA and post-ACA year. The average treatment effect is computed using the coefficients from the event study regression and the baseline value of newly eligibility share in each county.

Table III: Regression Results– Effect of ACA Expansion on County-level Per Capita Medicaid Transfers: Heterogeneity by Newly Eligible Population Share

	PC Medicaid Linear Model	PC Medicaid Quadratic Polynomial Model	PC Medicaid Linear Spline knot at the median of eligibility	PC Medicaid Quantile Model
ACA	-238.55***	-236.14**	-200.34***	153.02***
	(34.20)	(101.31)	(40.98)	(8.97)
ACA*Eligibility	12,212.82***	12,108.86***	11,155.30***	
	(748.01)	(4,589.99)	(1,097.13)	
ACA*Eligibility Sq		954.75		
		(45,457.54)		
ACA*Eligibility Spline			2,496.79	
			(3,219.55)	
ACA*Eligibility Quant 1				-35.58***
				(13.63)
ACA*Eligibility Quant 2				99.24***
				(22.24)
ACA*Eligibility Quant 3				304.88***
				(24.79)
ACA*Eligibility Quant 4				390.67***
				(32.25)
ACA*Eligibility Quant 5				744.61***
				(53.92)
Constant	1,268.88***	1,268.88***	1,268.87***	1,266.82***
	(1.54)	(1.54)	(1.54)	(1.52)
R^2	0.91	0.91	0.91	0.91
N	50,983	50,983	50,983	51,391

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

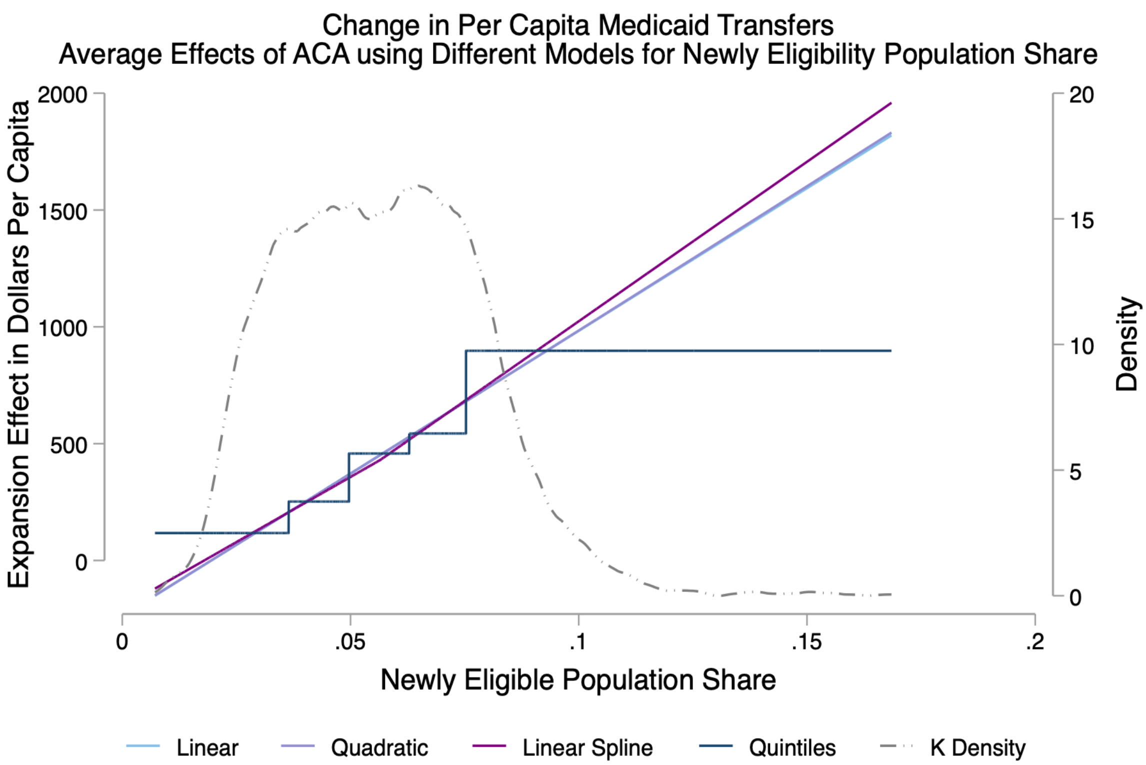
Note: Standard Errors in parentheses. County and year fixed effects are included in all models. ACA is the interaction between the relevant post-expansion year (2014-2016) and counties in expansion states (Post*Expansion). 50,983 county*year observations. The Newly Eligible Population share indicates the share of the county's population that would become eligible for Medicaid after expansion (includes non-disabled non-elderly childless adults below the 138% of the Federal Poverty Line.) The fifth quantile is the reference group. Standard errors are clustered at the county level.

Table IV: Average Treatment Effects Corresponding to Models

	(1) Linear Model	(2) Quadratic Polynomial Model	(3) Linear Spline - knot at the median of eligibility	(4) Model with dummies for eligibility quantiles	Observations (Counties)
ATE	456	456	456	451	3,023
Std Error	17	18	17	16	
Std Dev.	262	262	269	268	
ATT	361	361	361	361	1,521
Std Error	14	14	14	14	
Std Dev.	247	247	247	249	
ATNT	554	554	555	543	1,502
Std Error	21	23	22	20	
Std Dev.	240	241	255	255	

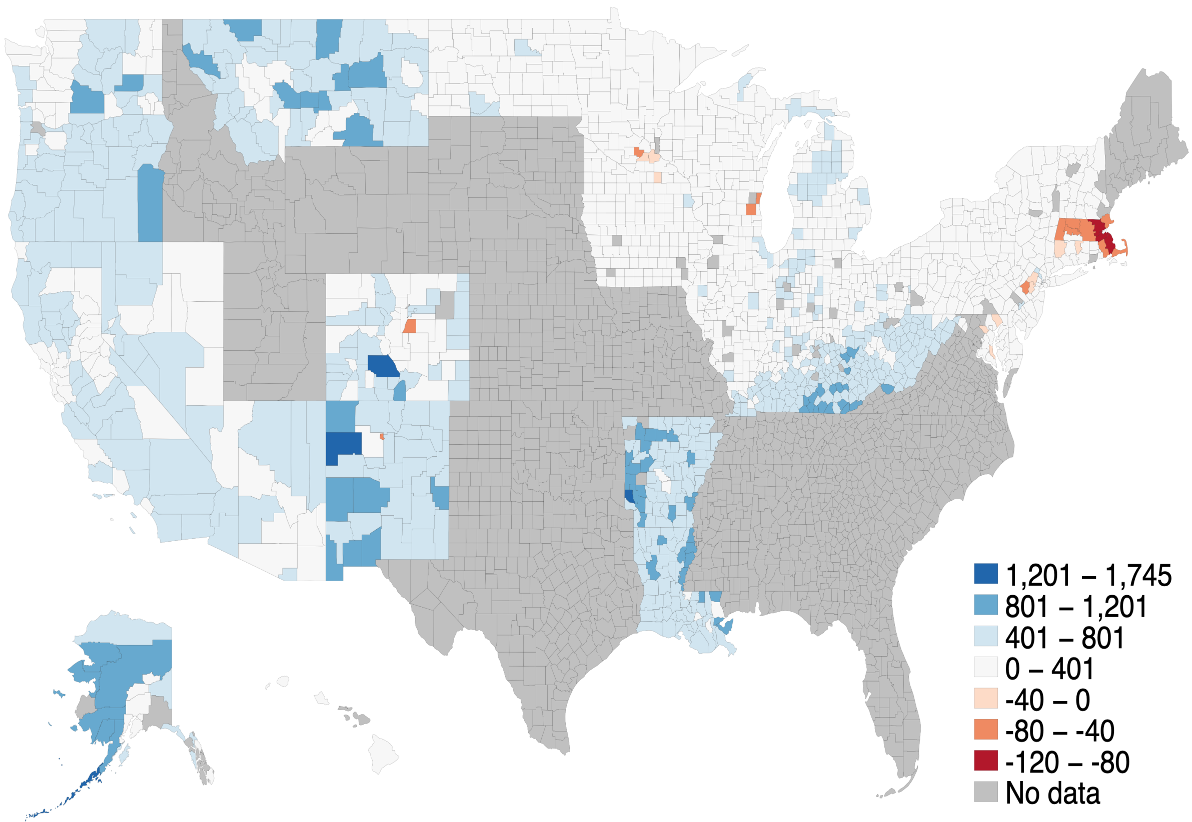
Note: Standard Errors and Standard Deviations shown below the means. Average Treatment Effect (ATE is the the average effect across all counties in both expansion and non-expansion states): increase in per capita Medicaid transfers caused by ACA (unweighted) averaged out across all counties. Average Treatment effect on the Treated (ATT is the average effect across the sub-set of counties that are located in expansion states): increase in per capita Medicaid transfers caused by ACA averaged out across counties in expansion states. Average Treatment effect on the Non Treated (ATNT is the average effect across all of the counties in non-expansion states): increase in per capita Medicaid transfers caused by ACA averaged out across counties in non-expansion states. We show treatment effects for each of our four specifications (Table III).

Figure V: Treatment Effect from the Three Models and Newly Eligible Population Share



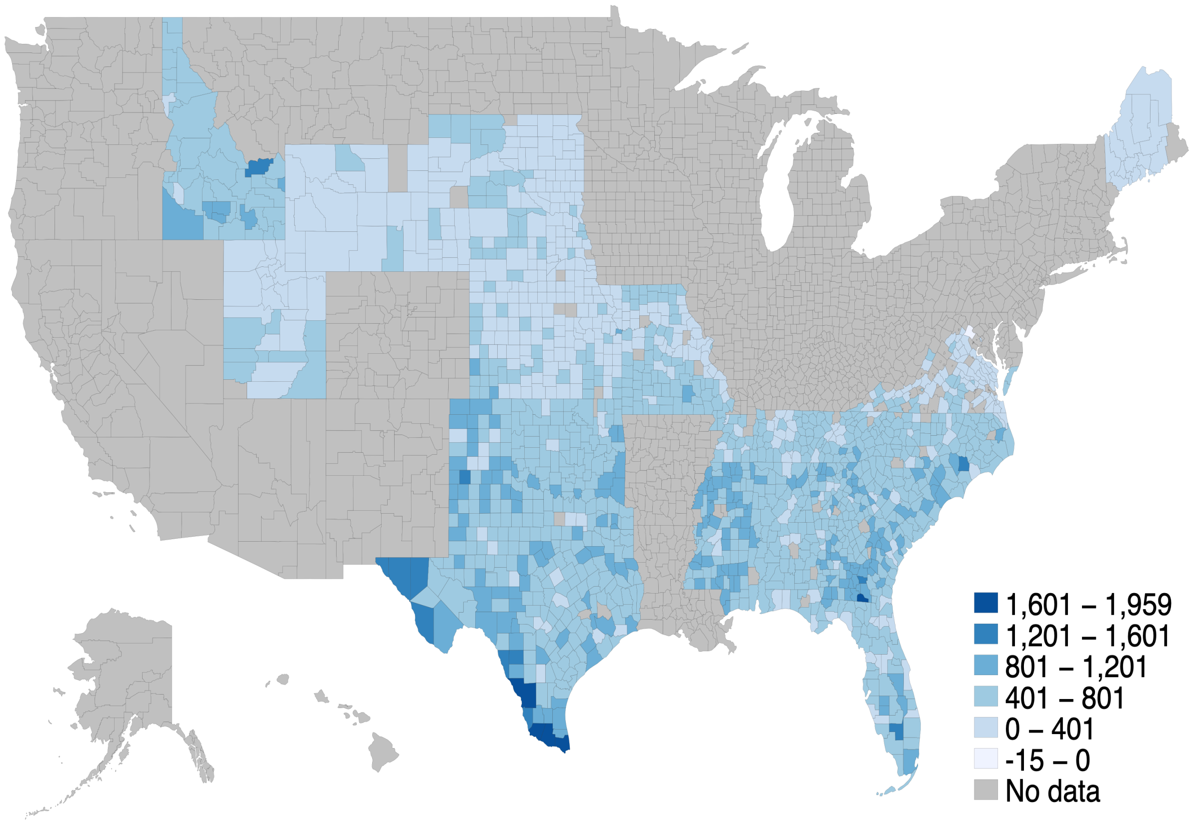
Note: We model 2010 county-level newly eligible share using specifications of different degrees of flexibility: linear, quadratic, linear spline, and quintiles. For each, we compute the average treatment effect (impact of the expansion on per capita Medicaid transfers). The models reach the best agreement where the density of the newly eligible shares is the highest, minimizing estimation error.

Figure VI: Transfer Effects of the ACA Expansion for Expansion States



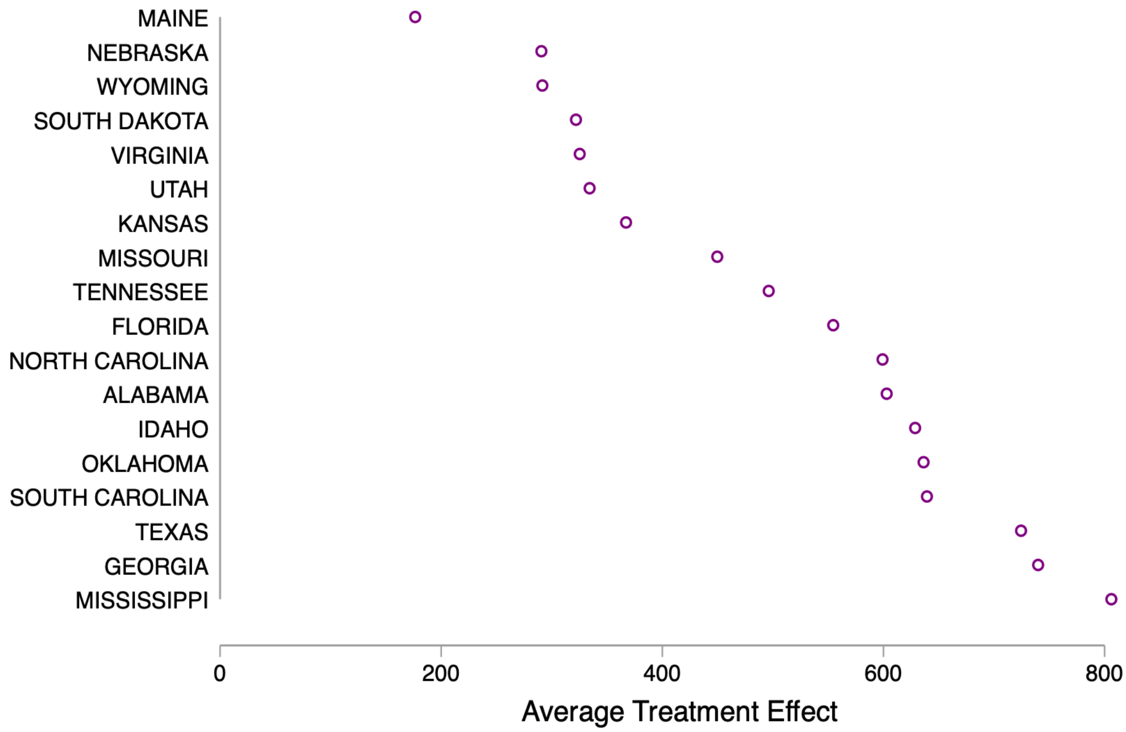
Note: We compute the impact of the ACA on Medicaid transfers exploiting the heterogeneity in newly eligible population share at the county level. We model the newly eligible variable using a linear spline specification and compute the average treatment effect. We plot the change in Medicaid transfers experienced by each county as a result of ACA in *expansion states* using data on the county-level newly eligible population share.

Figure VII: Transfer Effects of the ACA Expansion for Non-Expansion States



Note: This map reproduces Figure VI for non-expansion states. We compute the *expected* impact of ACA on Medicaid transfers, exploiting the heterogeneity in newly eligible population share at the county level. We model the newly eligibility variable using a linear spline specification and compute the *forecasted* average treatment effect. We plot the change in Medicaid transfers that each county would experience if their state would expand using 2010 data on the share of the population that would be newly eligible after the expansion. The only county in a non-expansion state associated with a negative transfer (i.e., -14.92 US Dollars) is Loudon County in Virginia.

Figure VIII: Forecasted Average Treatment Effects for Non-Expansion States



Note: We plot the average treatment effect for states that did not expand Medicaid. States are ranked from lowest to highest estimated county-level Medicaid transfers in case of expansion, based on their share of newly eligible individuals. For the predicted amount of county-level transfers received by the average county, Maine ranked the lowest and Texas the highest.

Table V: ACA Impact on Medicaid Transfers by Baseline Eligibility Rate, by Navigator Funding, and by Medicaid-Medicare Fee Ratio

	PC Medicaid Linear	PC Medicaid Quadratic	PC Medicaid Linear Spline	PC Medicaid Quantile
ACA	-350.9***	-383.6	-537.8***	1,221.3***
	(108.8)	(514.3)	(150.7)	(160.7)
ACA*pc Navigator	14,490.5***	-57,748.4***	-36,370.4***	
	(3,255.9)	(12,371.9)	(8,140.7)	
ACA* Eligibility	12,186.1***	31,926.6***	20,351.0***	
	(1,318.0)	(6,588.9)	(1,539.0)	
ACA*Medicaid Medicare fee	-213.3*	62.0	428.1***	
	(113.1)	(1,544.5)	(165.9)	
ACA*pc Navigator sq		1,541,204.2***		
		(322,429.4)		
ACA* Eligibility Sq		-159,101.0**		
		(68,442.8)		
ACA*Medicaid Medicare fee Sq		-136.4		
		(1,060.9)		
ACA * pc Navigator (Median)			76,681.3***	
			(11,215.9)	
ACA*Eligib (Median)			-12,858.8**	
			(6,340.2)	
ACA * Medicaid Medicare fee (Median)			-1,403.7**	
			(553.8)	
ACA*Eligibility Quant 1				-790.1***
				(100.4)
ACA*Eligibility Quant 2				-506.7***
				(105.5)
ACA*Eligibility Quant 3				-329.8***
				(101.5)
ACA*Eligibility Quant 4				-383.4***
				(106.0)
ACA*Low pc Navigator				-564.7***
				(118.6)
ACA * Medicaid Medicare fee Quant 1				96.2**
				(38.4)
ACA * Medicaid Medicare fee Quant 2				278.9***
				(49.3)
ACA * Medicaid Medicare fee Quant 3				130.3***
				(42.0)
Constant	1,348.5***	1,347.7***	1,347.6***	1,348.2***
	(2.7)	(2.7)	(2.8)	(2.7)
R^2	0.89	0.89	0.89	0.89
N	46,809	46,809	46,809	46,809

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Note: Standard Errors clustered at the county level are in parentheses. County and year fixed effects are included in all models. Baseline county eligibility rate from 2010, state navigator funding from 2016, and state Medicare-Medicaid fee ratios from 2008-2012 averages.

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

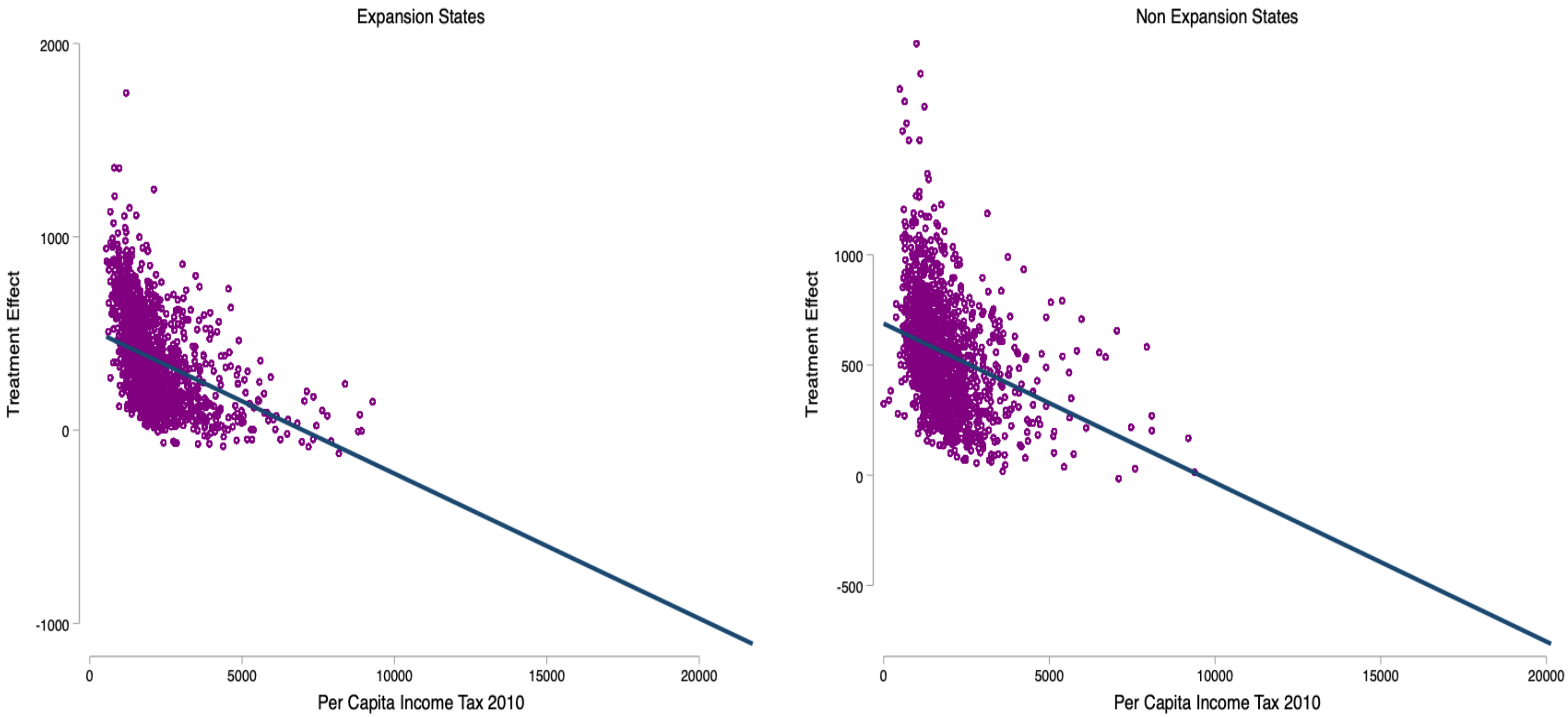
ACA is the interaction between Post Expansion and Counties in Expansion States (Post*Expansion). The ACA dummy switches on for counties in expansion states in 2014, 2015, or 2016. The years considered for the per capita Medicaid transfers and Newly Eligible Population are between 2001 and 2017. The three main covariates we use are baseline county eligibility rate from 2010, state navigator funding from 2016, and state Medicare-Medicaid fee ratios (2008-2012 average). Newly Eligible Population share indicates the share of the population that would become eligible for Medicaid after the expansion. The share includes non-disabled non-elderly childless adults below 138% of the federal poverty line. In column 4, the reference groups are eligibility quantile 5, per capita navigator high quantile, and Medicaid Medicare fee ratio quantile 5. The sample size results are from year*county.

Table VI: Average Treatment Effects from Models Using Navigator Funding and Medicaid Fee Ratios

	(1) Linear Model	(2) Quadratic Polynomial Model	(3) Linear Spline - knot at the median of eligibility	(4) Model with dummies for eligibility quantiles	Observations (Counties)
ATE	349	300	305	338	2,229
Std Error	26	24	24	25	
Std Dev.	253	217	211	252	
ATT	208	204	205	206	883
Std Error	16	15	15	15	
Std Dev.	219	228	223	219	
ATNT	441	362	371	424	1,346
Std Error	35	33	33	33	
Std Dev.	231	185	174	235	

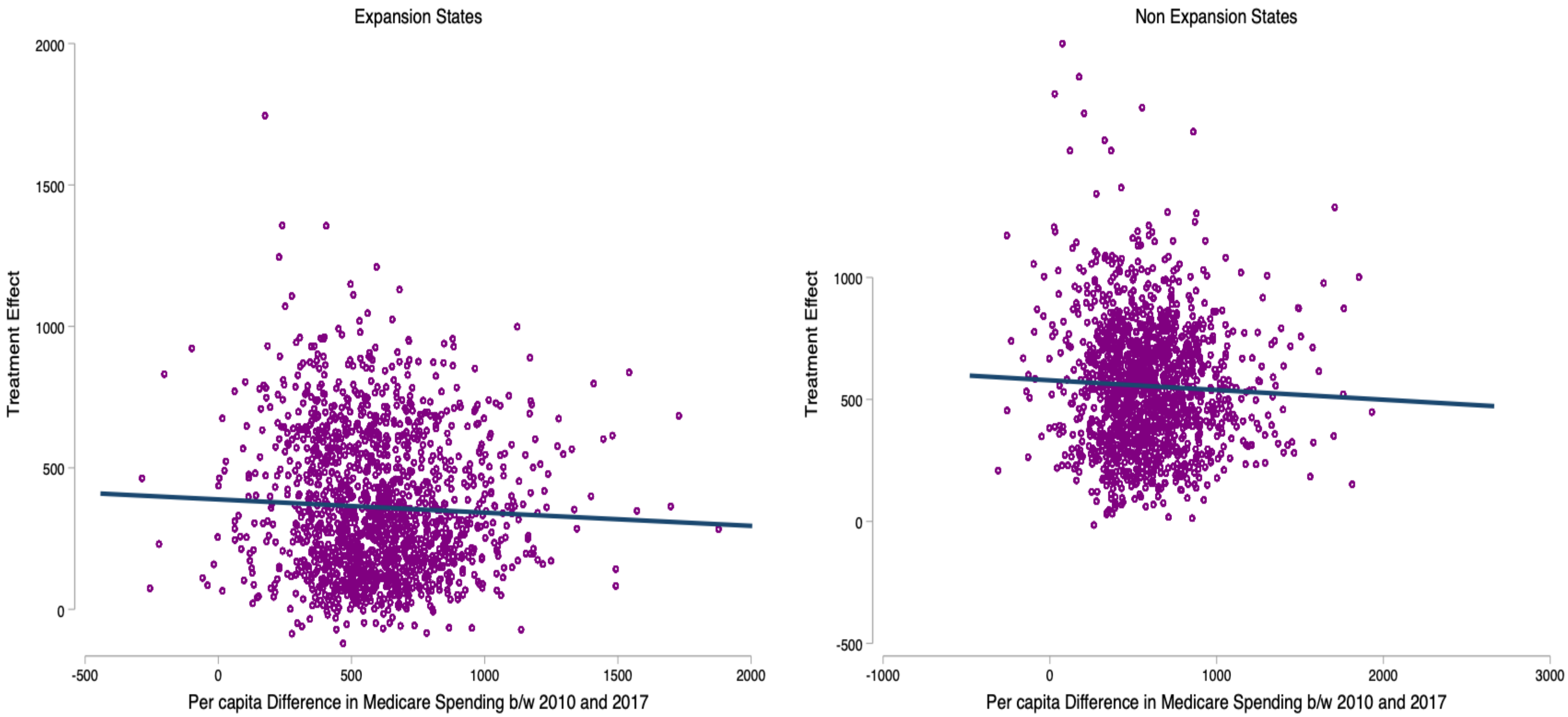
Note: Standard errors and standard deviations shown below the means. Treatment effects missing for counties with missing data on state navigator funding. We show treatment effects for each of the four different specifications in Table V, which, in addition to newly eligible share, include 2016 per capita navigator funding and Medicare Medicaid fee ratio (2008-2012 average). We compare different treatment effects estimates to Table IV. ATE, ATT, and ATNT should be interpreted as in Table IV.

Figure IX: The Relationship between Average Treatment Effect and Per Capita Income Tax



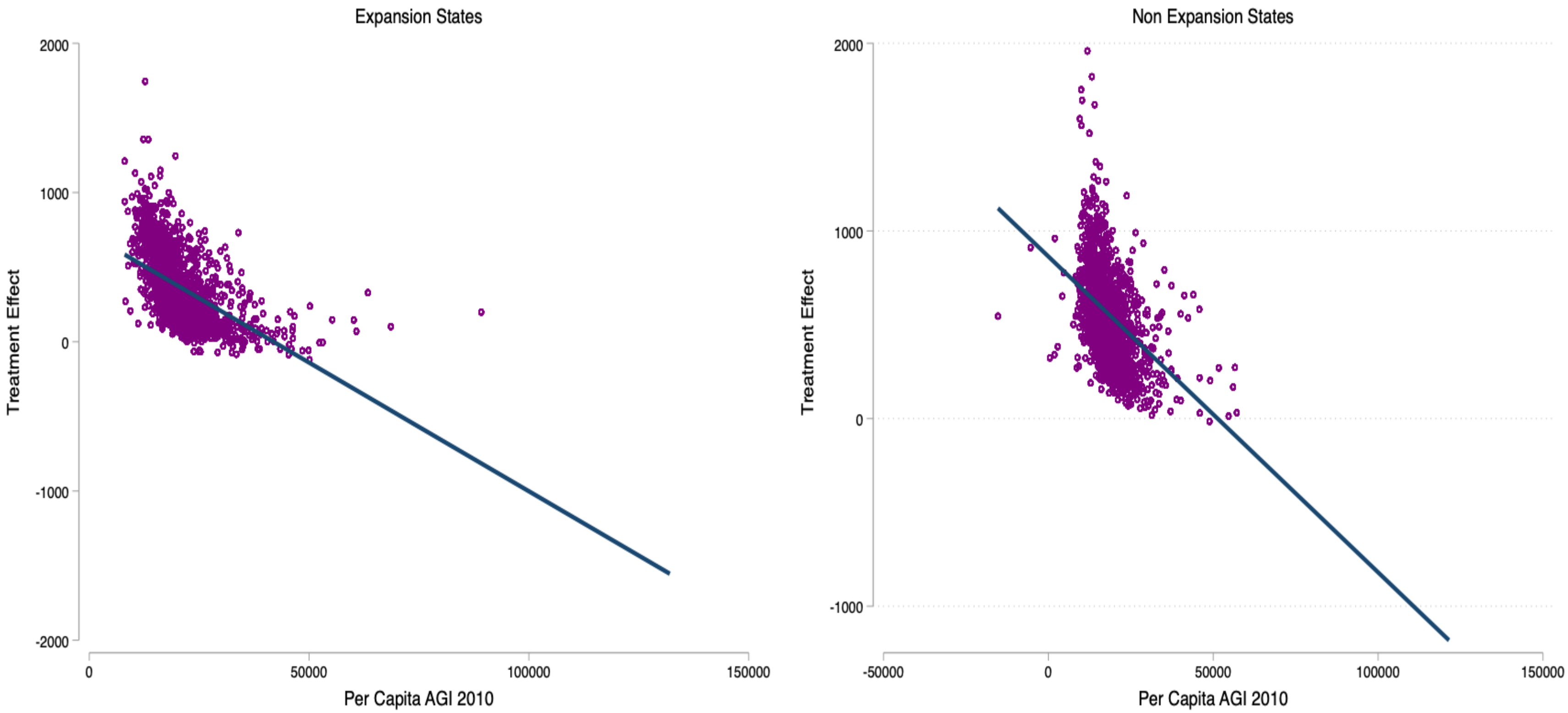
Note: This figure shows the scatterplot at the county level between the 2010 average per capita income tax paid by individuals in a county and the estimated average per capita Medicaid transfers that the individuals in a county received (expansion states on the left panel) or should receive (non-expansion states on the right panel) as a result of the ACA.

Figure X: The Relationship between Average Treatment Effect and the 2017-2010 Per Capita Difference in Medicaid Spending



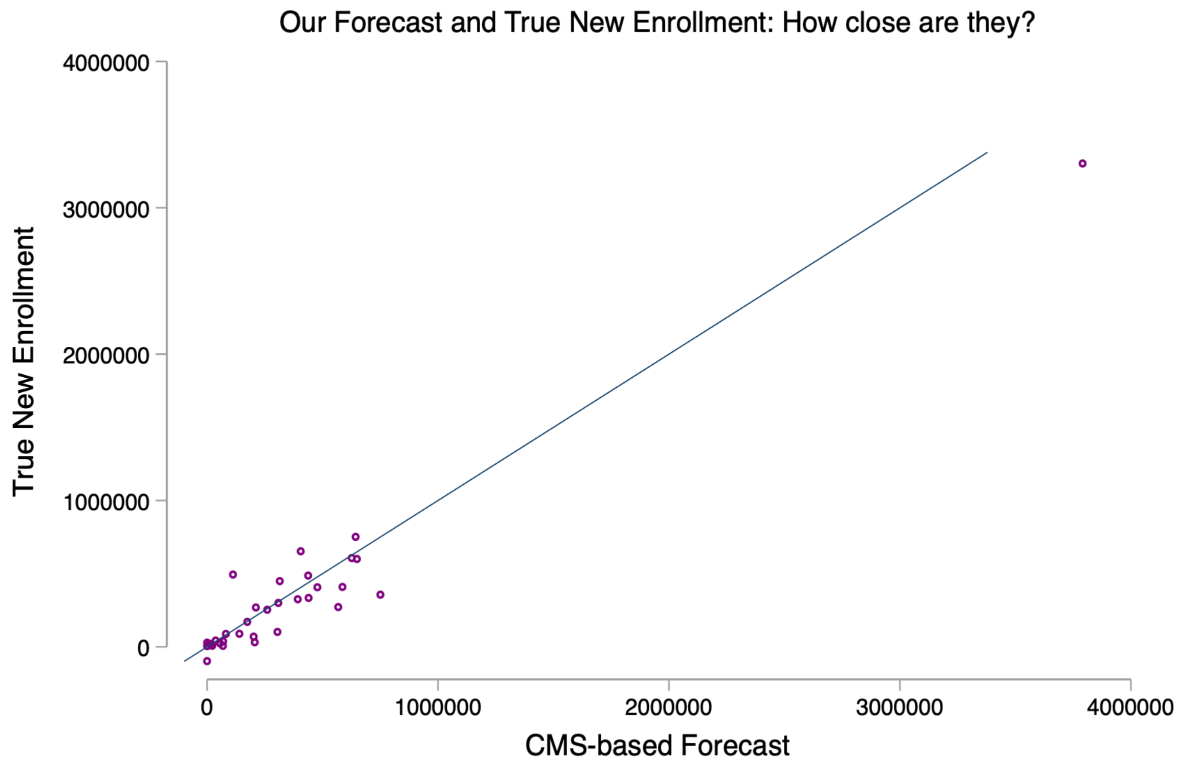
Note: This figure shows the scatterplot at the county level between the 2010 average per capita income tax paid by individuals in a county and the difference in per capita Medicare spending between 2010 and 2017, both in states that expanded Medicaid in 2014, 2015, or in 2016 (on the left panel) and in those that have not (on the right panel). To improve the visibility of the scatterplots, we drop all counties with an AGI above the 90th percentile (i.e. AGI = 4826385).

Figure XI: The Relationship between Average Treatment Effect and the Adjusted Gross Income



Note: This figure shows the scatterplot at the county level between the 2010 per capita adjusted gross income received by individuals in a county and the estimated average per capita Medicaid transfers that the individuals in a county received (expansion states on the left panel) or should receive (non-expansion states on the right panel) as a result of the ACA.

Figure XII: State-Level Enrollment-Forecasts Versus Actual



Note: We plot 2017 state-level enrollment numbers for the newly eligible published by the Centers for Medicare and Medicaid Services (Truffer et al., 2018) against the forecast state-level enrollment numbers that we obtained using our transfer estimates and a 2017 constant average cost from the CMS (i.e. $5,669). 45-degree line included for ease of interpretation. Pearson correlation coefficient between the two measures is equal to 0.9733.

Table VII: The Imputed Average Increases in County-Level New Enrollees as a Result of the ACA across Counties: In All States, Expansion States, and Non-Expansion States

Forecasted County-Level New Enrollees on Newly Eligible

	(1) Linear Model	(2) Quadratic Polynomial Model	(3) Linear Spline - knot at the median of eligibility	(4) Model with dummies for eligibility quantiles	Observations (Counties)
ATE	7,325	7,325	7,325	7,325	2,999
Std Dev.	35,072	35,072	35,072	35,072	
ATT	7,256	7,256	7,256	7,256	1,520
Std Dev.	39,936	39,936	39,936	39,936	
ATNT	7,395	7,395	7,395	7,395	1,479
Std Dev.	29,256	29,256	29,256	29,256	

Note: Standard deviations below means. We use the county-level estimates of Medicaid transfers from our regression on Table III and summarized in Table IV; we multiply these county-level transfer effects by the 2010 county population to estimate the total dollar transfers received by the county as a result of the ACA. We further divide by the CMS estimate of the average expenditure per newly eligible enrollee in 2017, $5,669 (Truffer et al., 2018), to estimate the number of new enrollees per county. Above, we report the ATE (average county), ATT (average expansion county), and ATNT (average non expansion county) estimates.

Table VIII: Imputed Average Per Capita Increases in County-Level Enrollment: In All States, Expansion States, and Non-Expansion States

Forecasted County-Level Enrollment Population Shares on Newly Eligible

	(1) Linear Model	(2) Quadratic Polynomial Model	(3) Linear Spline - knot at the median of eligibility	(4) Model with dummies for eligibility quantiles	Observations (Counties)
ATE	.08	.08	.081	.08	3,023
Std Dev.	.046	.046	.047	.047	
ATT	.064	.064	.064	.064	1,521
Std Dev.	.044	.044	.044	.044	
ATNT	.098	.098	.098	.096	1,502
Std Dev.	.042	.042	.045	.045	

Note: Standard Deviations below averages. We use our county-level estimates of Medicaid transfers obtained from Table III and summarized in Table IV. We divide them by the CMS average expenditure estimate per newly eligible enrollee in 2017, $5,669 (Truffer et al., 2018), to estimate the population share of new enrollees at the county level. Above, we report the ATE (average county), ATT (average expansion county), and ATNT (average non expansion county) estimates.

9 Alternative Method for County-level Enrollment Estimates

Introducing State-Level Heterogeneity in Average Cost

Table IX: The Imputed Average Per capita Increases in County Level Enrollment as a result of ACA across all Counties, Counties in Expansion States, and Counties in Non-Expansion States - Average Cost State-Level Heterogeneity

Forecasted County-Level Enrollment Numbers on Newly Eligible - State-Level Heterogeneous Average Cost

	(1) Linear Model	(2) Quadratic Polynomial Model	(3) Linear Spline - knot at the median of eligibility	(4) Model with dummies for eligibility quantiles	Observations (Counties)
ATE	7,062	7,062	7,051	6,931	2,925
Std Dev.	47,628	47,636	47,920	52,971	
ATT	7,042	7,040	6,971	7,175	1,423
Std Dev.	61,753	61,746	61,777	71,249	
ATNT	7,080	7,083	7,127	6,699	1,502
Std Dev.	28,010	28,051	28,922	25,626	

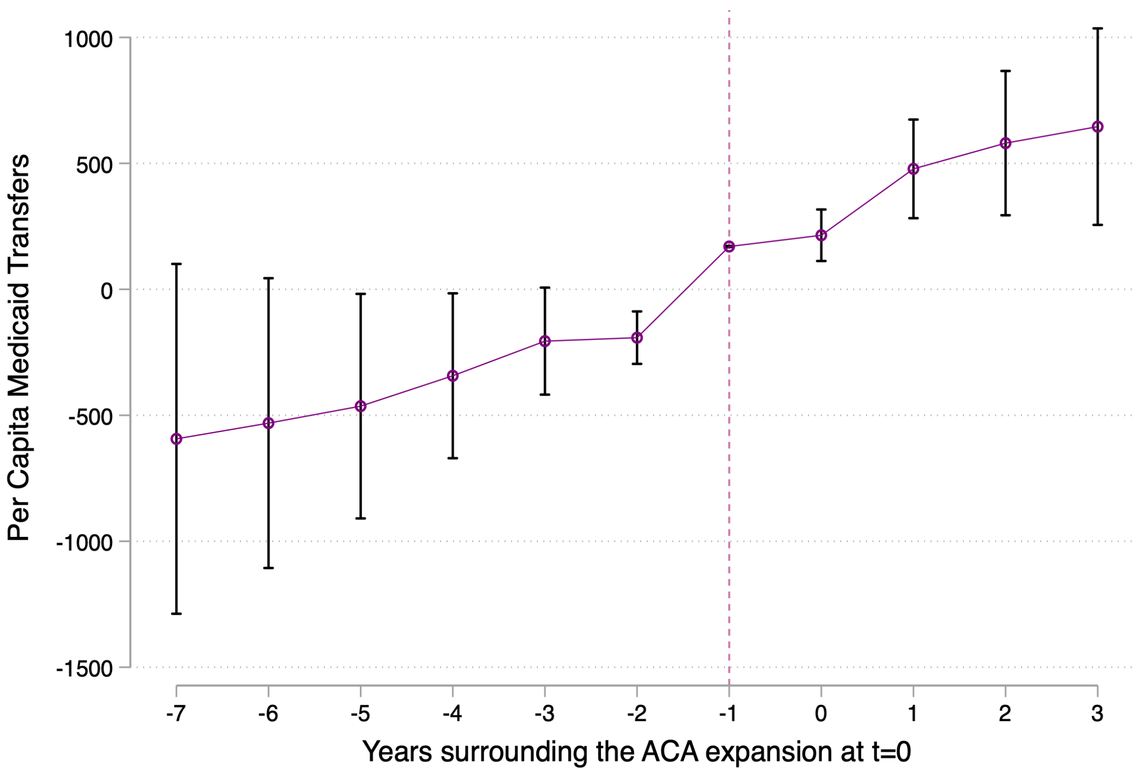
Note: Standard Deviations below Averages. We use our county level estimates of Medicaid transfers obtained from regression on Table III and summarized in Table IV, and we multiply such county level transfer effects by the 2010 county's population, so to obtain an estimate of the total dollar transfers received by the county as a result of the ACA (using population at baseline year). However, we now use a different computation for the per-new-enrollee average cost. For expansion states, use state-level enrollment numbers by the CMS (specifically, Total Group 8 newly eligible enrollment) in 2017. Then, we found estimates of the federal expenditures on newly eligibles by state in 2017. By dividing the total state-level expenditures on newly eligibles by the number of new enrollees, we obtain a state level average cost for expansion states. For non-expansion states, we use the mean of such average cost instead. Dividing the total federal transfers to each county by this differently computed average cost, we obtain the numbers above. We show results for the average county (ATE), the average county in expansion states (ATT), and the average county in non-expansion states (ATNT).

10 Appendix

11 Comparative Interrupted Time Series

We implemented the comparative interrupted time-series (CITS) specification following the spirit of Steinberg and Anglum (2003). In particular, we augment our event-study model by allowing for flexible differential pre-trends that vary with counties' baseline exposure to the ACA expansion. Specifically, we interact the pre-ACA eligibility rate with both a linear and a quadratic polynomial in calendar time. These terms, $eligibility_i \times t$ and $eligibility_i \times t^2$, enable counties with higher eligibility shares to follow not only steeper but also nonlinear outcome trajectories before the expansion. By absorbing both the slope and curvature of pre-expansion differences, this quadratic CITS approach more rigorously isolates post-expansion changes that can be attributed to Medicaid expansion rather than to pre-existing dynamic trends. The resulting estimates remain qualitatively similar to our baseline event-study results, indicating that the modest pre-trend differences observed in Figure IV do not materially drive our main conclusions.

Figure XIII: Event Study with Separate Time Trends by Baseline Eligibility



12 Main Analysis using only states without missing data on Navigator Funding and Medicaid Medicare fee ratio

Table X: Regression Results– Effect of ACA Expansion on County-level Per Capita Medicaid Transfers: Heterogeneity by Newly Eligible Population Share - States with data on Navigator Funding and Medicaid Medicare fee ratio

	PC Medicaid Linear Model	PC Medicaid Quadratic Polynomial Model	PC Medicaid Linear Spline knot at the median of eligibility	PC Medicaid Quantile Model
ACA	-344.83***	-563.71***	-454.72***	136.15***
	(53.67)	(119.46)	(51.13)	(9.55)
ACA*Eligibility	11,905.84***	21,143.73***	14,860.02***	
	(1,264.91)	(5,483.88)	(1,417.33)	
ACA*Eligibility Sq		-85,637.71		
		(57,248.90)		
ACA*Eligibility Spline			-7,537.32	
			(5,295.15)	
ACA*Eligibility Quant 1				-141.24***
				(13.32)
ACA*Eligibility Quant 2				73.17***
				(25.52)
ACA*Eligibility Quant 3				238.86***
				(26.82)
ACA*Eligibility Quant 4				201.72***
				(43.33)
ACA*Eligibility Quant 5				577.70***
				(105.57)
Constant	1,229.89***	1,229.89***	1,229.88***	1,227.56***
	(1.20)	(1.19)	(1.19)	(1.19)
R^2	0.90	0.90	0.90	0.90
N	37,893	37,893	37,893	38,301

* $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

Note: Standard Errors in parentheses. ACA is the interaction between the relevant post expansion year (2014-2016) and counties in expansion states (Post*Expansion). 38,845 county*year observations (17 years, 2001-2017, by 2,285 counties). Only states without missing data on Navigator Funding and Medicaid Medicare fee ratio have been used. The Newly Eligible Population share indicates the share of the county's population that would become eligible for Medicaid after expansion (includes non-disabled non-elderly childless adults below the 138% of the Federal Poverty Line.) The fifth quantile is the reference group. Standard errors are clustered at the county level.

Table XI: Average Treatment Effects Corresponding to Models - Only states with data on Navigator Funding and Medicaid Medicare fee ratio

	(1) Linear Model	(2) Quadratic Polynomial Model	(3) Linear Spline - knot at the median of eligibility	(4) Model with dummies for eligibility quantiles	Observations (Counties)
ATE	341	331	330	324	2,253
Std Error	25	27	30	25	
Std Dev.	252	223	223	235	
ATT	207	206	206	206	884
Std Error	15	15	15	15	
Std Dev.	206	207	206	201	
ATNT	429	414	411	400	1,369
Std Error	33	38	41	33	
Std Dev.	241	193	195	223	

Note: Standard Errors and Standard Deviations are shown below the means. Average Treatment Effect (ATE): increase in per capita Medicaid transfers caused by ACA (unweighted) averaged out across all counties. Average Treatment effect on the Treated (ATT): increase in per capita Medicaid transfers caused by ACA averaged out across counties in expansion states. Average Treatment effect on the Non Treated (ATNT): increase in per capita Medicaid transfers caused by ACA averaged out across counties in non-expansion states. We show treatment effects for each of our four specifications (Table X). These results are obtained using only states with data on Navigator Funding and the Medicaid Medicare fee ratio.