State Responses to Federal Matching Grants: The Case of Medicaid*

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Abstract

While Medicaid is currently financed by open-ended matching, in which the federal government pays an uncapped percentage of program expenditures, there has been interest in transforming the financing structure to block grants, which limits federal cost-sharing to a fixed amount. To understand the implications of this reform, I measure the effect of match rates on Medicaid spending by using the variation induced by a kink in the match rate formula. I find that a percentage point increase in the federal match raises per-beneficiary spending by 3 percent. Using this estimate, I discuss the welfare impact of a block grant reform.

Keywords: Medicaid, matching grants
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1 Introduction

Social assistance programs in the United States are funded and administered by different levels of government, with some programs involving only one level of government and others entailing partnerships between local, state, and federal governments. Cash welfare is funded by a conditional block grant from the federal to state governments, food assistance vouchers are paid for entirely by the federal government, and Medicaid is funded by a matching grant from the federal to the state governments. While the theoretical implications of these arrangements for program spending are clear, the empirical magnitudes often remain unexplored. In particular, for the largest means-tested program, Medicaid, few attempts have been made to estimate how its current financing structure, open-ended matching, affects expenditures. Yet, there have been repeated calls to reform the Medicaid financing system. Understanding how the current matching structure impacts program spending is crucial for analyzing the potential consequences of a reform.

Since its inception in 1965, the Medicaid program, which provides health insurance to the poor, is jointly financed by the state and federal governments. With the condition that state programs meet minimum eligibility and coverage requirements, the federal government matches state Medicaid expenditures at a rate that depends inversely on the state’s per-capita income. As a result, states are responsible for no more than 50 percent and as little as 17 percent of total Medicaid costs. Importantly, there is no limit to the amount of funds the states can draw from the federal government. From the perspective of state governments, the matching grant is substantial as Medicaid is the largest single category of expenditures in states’ budgets, accounting for 29 percent in 2019 (NASBO, 2020). The grant is also increasingly substantial for the federal government. Between 1985 and 2019, total Medicaid expenditures more than tripled in real terms, with a recent average federal contribution of about 64 percent (MACPAC, 2020a). And with federal Medicaid costs projected to reach $730 billion by 2030, there has been substantial interest among some policymakers in limiting the federal government’s contribution to Medicaid by turning the open-ended matching grant into a block grant, in which each state receives a capped amount of funds from the federal government to finance their state Medicaid programs (CBO, 2020).

Block-granting Medicaid has been a perennial cause since the 1980s. In 1981, President Reagan first proposed capping federal funds to the Medicaid program on the grounds that states, which are closer to the people, are more likely to cost-effectively deliver the services demanded by its residents if given the flexibility to do so. Though this proposal did not pass Congress, the issue came up again in 1995, when
House Speaker Newt Gingrich proposed the “Medigrant” program, which sets caps on federal Medicaid funding based on measures of state needs. This plan passed Congress, but was vetoed by President Clinton. In 2003, President Bush proposed a plan in which states could choose to accept block grants that, in the short-term, would be larger than current matching grants, but subsequently shrink to achieve ten-year budget neutrality. This plan failed to materialize, as did Congressman Paul Ryan’s 2012 block grant proposal and the 2017 American Health Care Act, which contained provisions to place “per-capita caps” on Medicaid spending. Most recently, President Trump’s 2020 Healthy Adult Opportunity initiative provides waivers to states that choose to block grant part of their Medicaid programs. While Medicaid is still currently financed by federal matching, the issue of block grants continues to be discussed in national policy circles.

From a theoretical perspective, a positive federal match incentivizes states to increase expenditures on Medicaid by lowering the marginal price: an extra dollar’s worth of Medicaid costs $(1-\theta)$ to the state, where $\theta$ is the match rate. As such, decreasing the match rate decreases Medicaid expenditures through both a substitution effect and an income effect. Under a block grant system, an extra dollar’s worth of Medicaid will cost exactly one dollar to the state, translating to an effective match rate of zero. Therefore, even if a block grant of the same size replaces a matching grant, expenditures on Medicaid will theoretically decrease (due to the substitution effect). As I demonstrate subsequently, the empirical magnitude of this spending response is an important input for predicting the potential effects of a Medicaid financing reform.

In this paper, I examine the question of how matching grants influence Medicaid spending by exploiting the exogenous variation in match rates created by a kink in the match rate formula. Since the state’s share of the costs depends on its per-capita income and is capped at 50 percent, the rate of change in the match rates as a function of income jumps discontinuously. The structure of the cost-sharing scheme lends itself to analysis via a regression kink design (RKD), formalized by Card et al. (2015). Specifically, if the match rate is a kinked function of state income, and we observe that spending on Medicaid is also a kinked function of state income at the same point, the ratio of the magnitudes of the kinks identifies a causal effect of match rates on spending. Using this method, I find that a one percentage point increase in the match rate increases spending per beneficiary by about $210 (3 percent), implying a spending elasticity of 1.6 with respect to the match rate. I find that this effect is primarily driven by spending in hospitals and long-term supports and services, with no evidence that the match rate affects the total number of Medicaid beneficiaries.

As mentioned above, the spending response to Medicaid match rates is largely unexplored in the literature. In the only study that directly examines this question, Adams and Wade (2001) find a Medicaid
price elasticity of -0.09, or an implied match rate elasticity of 0.16.\textsuperscript{1} This estimate is obtained using a state fixed effects model on data from the late 1980s and early 1990s. However, since match rates are inversely related to state per-capita income, the within-state variation in match rates used may be related to Medicaid spending and downwardly bias estimates.

Although there are few studies that examine the effect of matching grants on Medicaid, there has been considerably more attention paid to its effects on Aid to Families with Dependent Children (AFDC), a related means-tested cash assistance program that was funded by open-ended matching and subsequently replaced in 1996 with block-grant-funded Temporary Aid for Needy Families (TANF). As is currently the case with Medicaid, a primary goal of measuring the match rate elasticity in this context was to anticipate the consequences or evaluate the effects of the switch from matching grants to block grants. Similar to Medicaid, one major difficulty for these studies is that, since 1958, at least some portion of the AFDC match rate depended on state per-capita income. Recognizing this early on, Orr (1976) estimates a price elasticity of -0.2 for the period 1963-72, but acknowledges the potential bias in a footnote. For comparison, my estimated price elasticity is -1.5.\textsuperscript{2} The same bias potentially plagues the estimates in Moffitt (1984) and Gramlich and Laren (1984), who find price elasticities of -0.1 (insignificant) and -1.1, respectively. Ribar and Wilhelm (1999) and Chernick (2000) summarize and attempt to reconcile the available estimates, but generally conclude that the results are very sensitive to specification and time period. Baicker (2005) addresses the problematic dependence of match rates on income by using the variation from grant schedule reforms over time to generate instruments for match rate changes, and finds a price elasticity of -0.4. While there are some similarities between AFDC and Medicaid, however, it is unclear whether this estimate from an earlier period (1950s) for a cash assistance program applies to the current Medicaid context.

Using my estimate of how Medicaid spending responds to the match rate, the final section of this paper considers the welfare implications of a switch to block grant financing. I start with a model that assumes that states are heterogeneous in their preferences for Medicaid, but that there exist positive interstate spillovers of Medicaid spending, a standard rationale for federal matching (see, e.g., Grannemann and Pauly, 1983; Brown and Oates, 1987; Wildasin, 1991). To incorporate realistic features of the actual matching system, the model further assumes a desire by the federal government to redistribute from richer to poorer states.\textsuperscript{1}

\textsuperscript{1}An earlier study by Grannemann (1980) also estimates a Medicaid price elasticity and finds a larger response of -0.78 for the 1970s, but does not provide enough information to separate out components of the price into parts associated with federal match rates and other factors, which is needed to calculate an implied match rate elasticity.

\textsuperscript{2}If $\epsilon_m$ is the match rate elasticity of spending, the price elasticity of spending is equal to $\epsilon_p = -\epsilon_m \cdot \frac{1}{1-\theta}$ where $\theta$ is the match rate.

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Although much depends on the specifics of the reform, the model suggests that a switch from matching grants to block grants has two potential effects: 1) a reduction in overall Medicaid spending, which may result in underprovision relative to the social optimum, and 2) a possible redistribution of funds across states that may be socially beneficial. The welfare impacts depend crucially on the valuation of Medicaid spillovers and the social welfare weights placed on each state, which I calibrate by assuming that the current matching system is socially optimal, similar to exercises by Bourguignon and Spadaro (2012), Gordon and Cullen (2012), and Lockwood and Weinzierl (2016) in the context of optimal taxation. I then simulate the spending responses and welfare impacts of block grant reforms similar to those suggested by Clemens and Ippolito (2018). In the benchmark case where the current allocation of matching grants is simply converted to block grants, I estimate that the grants must be 41 percent larger to maintain social welfare.

Finally, while this paper focuses on using the Medicaid match rate elasticity to understand the implications of a switch to a block grant system, there are other potential reforms of interest that could be better understood using the estimates in this paper. In their study of potential reform options, Grannemann and Pauly (1983) discuss other changes to the match rate formula including closed-ended (i.e., capped) matching grants, match rates that depend on measures of fiscal capacities other than state income, and match rates that decline with benefit levels. In addition, although most of the discussion here focuses on a potential reduction in match rates, the estimates may also be informative of the impact of increased match rates, which was a prominent feature of the Medicaid expansions in Patient Protection and Affordable Care Act (ACA) of 2010. The ACA provided increased federal match rates for expanding coverage to low-income adults, as well as for certain service categories, including some preventative care and home- and community-based care.

The remainder of the paper is organized as follows: Section 2 will briefly give the details of how Medicaid is financed in the United States. I lay out my econometric strategy in Section 3 and describe the data I use in Section 4. Section 5 contains my estimation results. In Section 6, I discuss the welfare implications of my estimates for Medicaid financing reform. Section 7 concludes.

2 Background on Medicaid Financing

Since its inception in 1965, Medicaid programs have been jointly financed by state and federal governments, with the federal government paying at least 50 percent of the costs. The federal government’s share is in the form of an open-ended (i.e., uncapped) matching grant, where the match rate is inversely related to the
income of the state. Specifically, the match rate, or the Federal Medical Assistance Percentage (FMAP), is determined by the following formula:

$$FMAP_s = \max\left\{ 0.5, 1 - 0.45 \left( \frac{PCPI_s}{PCPI_{US}} \right)^2 \right\}$$

where $s$ denotes the state, $PCPI_s$ is the per-capita personal income of the state, and $PCPI_{US}$ is the national per-capita personal income. While the FMAP is also capped at 83 percent (not reflected in the formula above), the upper limit does not bind for any state during my sample period, 1985-2013. This match rate is used to determine the federal share of most medical expenses incurred by enrollees of the state’s traditional Medicaid program under Title XIX of the Social Security Act.\(^3\) Each state’s FMAP is updated annually and published in the Federal Register about one year in advance of when the matching rate will take effect.\(^4\) To ensure that match rates do not experience large year-to-year jumps, the average per-capita personal income (PCPI) over the most recent three years is used in the formula.\(^5\)

Although the federal match rate is usually determined by the formula above, there are exceptions for state fiscal relief during downturns. As part of the Jobs and Growth Tax Reconciliation Act of 2003, each state’s FMAP was first held harmless (not allowed to decrease) and then increased by 2.95 percentage points for the last two quarters of the 2003 fiscal year and the first three quarters of the 2004 fiscal year. During the Great Recession, the American Recovery and Reinvestment Act of 2009 held all states’ FMAP harmless and increased FMAPs by 6.2 percentage points or more, depending on the state’s unemployment rate, from October 1, 2008 to December 31, 2010.

There are also some state-specific deviations from the regular match rate formula. Alaska’s FMAP was delinked from the state’s income by the 1997 Balanced Budget Act, where it was argued that the state’s PCPI was a “poor and inadequate measure of the states’ needs and abilities to participate in the Medicaid program” (Miller and Schneider, 2004). Alaska’s FMAP was raised from 50 percent to 59.8 percent for two years and then determined by a modified formula thereafter. In addition, Louisiana’s match rate was increased above their regular rate (with a cap on federal funds) due to state budgetary shortfalls for fiscal

\(^3\) Expenses under the Children’s Health Insurance Program (CHIP), established by Title XXI, are matched at a higher rate and federal funding is capped. Expenses of the newly eligible adult group as part of the Affordable Care Act are also matched at a higher rate.

\(^4\) Prior to 1987, the FMAP was updated every two years.

\(^5\) Since FMAPs are published a year in advance of the fiscal year in which they are applied, the PCPI measure used to determine each year’s FMAP corresponds to that of three years prior. For example, the FMAP for the fiscal year 2008 (i.e., October 2007 through September 2008) is determined by the average PCPI in 2003-2005.
years 1996-97.

3 Empirical Strategy

As discussed above, the Medicaid match rate for each state is a function of its per-capita income. Therefore, if one were to simply regress expenditures on the match rate, to the extent that poorer states have smaller tax bases and therefore less room in their budget for Medicaid, the estimated match rate effect may be attenuated or even reversed. However, once state per-capita income is included as a control in such a regression, it is then not clear what variation is used for identification. In this paper, I exploit the quasi-experimental variation in match rates that stems from the 50 percent floor, using a regression kink design (Card et al., 2015).

The idea behind a regression kink design is similar to that of a regression discontinuity design (RDD). If I observe a discontinuous rate of change in the Medicaid match rate with respect to per-capita personal income, and then correspondingly a discontinuous rate of change in Medicaid spending per beneficiary with respect to the same per-capita personal income measure, the ratio of these two discontinuities identifies a causal effect of match rates on Medicaid spending. Formally, let $B = b(\theta, M, U)$ be a state’s Medicaid expenditures. $B$ is determined by three factors: 1) the Medicaid match rate $\theta$, 2) the per-capita income $M$, and 3) an unobservable state-specific error term $U$. Suppose further that the match rate $\theta = \theta(M)$, where $\theta(\cdot)$ is a known, continuous, but kinked function of the state’s income $M$, where the kink point is normalized to be at $M = 0$. I am interested in $\frac{\partial b(\theta(m, u))}{\partial \theta}$, the causal effect of the match rate on Medicaid expenditures.

As shown in Card et al. (2015), given the kinked function of per-capita income that determines match rate, the key condition for identification of a causal effect is the smoothness of the conditional density of match rates, $f_{\theta|U}(\theta|u)$, through the threshold for all $u$. When this condition is met, along with other regularity conditions, the following causal effect is identified:

$$E \left[ \frac{\partial b(\theta(0), 0, u)}{\partial \theta} \right| M = 0] = \lim_{m \to 0^-} \frac{\partial E[B|M=m]}{\partial m} - \lim_{m \to 0^+} \frac{\partial E[B|M=m]}{\partial m}$$

As with the RDD, much of the appeal of RKD comes from the testability of its key assumptions. The key condition listed above lends itself easily to an empirical test: A plot of the density of matching rates with respect to the running variable, per-capita personal income, should not exhibit any discontinuities or kinks.
I show that this is indeed the case in Appendix Figure A.1.

I use local polynomial regressions to estimate the RKD causal parameter. Specifically, I fit Medicaid spending and other outcome measures as local polynomial functions of relative per-capita income that are allowed to differ on each side of the kink threshold, and the numerator of equation (1) is estimated as the slope change at the threshold. Although the slope change in the denominator is in principle known from the FMAP formula, there are some deviations during economic downturns as discussed above, warranting the use of a “fuzzy” RKD design, wherein the denominator of (1) is estimated analogously via local polynomial regressions. I follow Card et al. (2015, 2017) in employing a uniform kernel, and I present estimates using both linear and quadratic functions of the running variable, relative per-capita income. Standard errors are clustered at the state level.

As is the case for implementing RDD, there is the question of which bandwidth to use for estimating the RKD effect (Lee and Lemieux, 2010; Imbens and Lemieux, 2008). Ideally, since I am estimating right around the kink point, I should only use observations whose values of the running variable are close to the kink point. However, doing so will limit the sample size and result in imprecise estimates. In my main results, I will therefore estimate the match rate effect using data of varying distances from the threshold, and show how sensitive these results are to the bandwidth selection.

Finally, note that while this empirical design hinges on match rate variation that applies only to certain states with per-capita income near the kink point and primarily compares across these states, it is practically the only variation that can be exploited because the match rate formula has largely remained the same since Medicaid’s inception. Other temporary changes in match rates are typically in response to economic conditions, as discussed above. In Appendix Section B, however, I estimate the impact of match rates using a different identification strategy that utilizes within-state match rate variation driven by updates to per-capita personal income calculations. This method produces much more imprecise, but not necessarily inconsistent, estimates of the effect of match rates on spending.

4 Data and Descriptive Statistics

To analyze the effect of match rates on state Medicaid programs, I use state-level data on Medicaid expenditures, beneficiaries, and per-capita personal income. Medicaid expenditure data for each state are obtained from the annual Financial Management Reports (FMR) published by the Centers for Medicare and Medi-
caid Services (CMS). The FMR data are derived from the CMS-64 form, which states submit to CMS on a quarterly basis. The CMS-64 must be filed by the state in order to receive federal funding for qualified expenses, and the expenditures reported must be backed up by actual invoices or cost records. Expenditures are broken down into federal and state shares and by different categories of spending. Since administrative costs, which account for about 5 percent of costs, are matched at a different rate from medical assistance payments, I examine only the latter. All expenditures are expressed in 2013 dollars, adjusted using the medical care index of the Consumer Price Index.

The number of beneficiaries, defined as individuals for whom Medicaid has made a payment in a fiscal year, for each state, are from CMS’s Medicaid Statistical Information System (MSIS) summary tables (through 2010) and MACStats reports prepared by the Medicaid and CHIP Payment and Access Commission (MACPAC) (for data after 2010).\(^6\) While it may be more natural to examine the number of Medicaid enrollees, enrollment data is not available before 1991 and is missing for some state-years thereafter. Furthermore, the count of the number of beneficiaries is somewhere in between the number of people who actually utilize Medicaid services and the number of people covered: starting in 1998, the measure includes managed care enrollees, regardless of whether the enrollee actually utilized Medicaid services. To account for these seams in the data, I show that my results are robust to including year fixed effects in the estimating equation.

State income measures are published by the Bureau of Economic Analysis (BEA) every year. Importantly, I use the per-capita personal income measures that are inputs for calculating the FMAP (i.e., the most recent three years of PCPI available at the time of FMAP publication). State demographic characteristics, annual unemployment rates, and poverty rates are from the March Current Population Survey (via the Integrated Public Use Microdata Series), the Bureau of Labor Statistics, and the Census Bureau, respectively.

My analysis sample covers the years 1985-2013. The endpoints of the sample period are driven primarily by availability of expenditure and beneficiary data, though the implementation of many provisions of the ACA in 2014, including increases in FMAP for certain spending categories, makes the latter a natural break point. Since, as mentioned above, Alaska’s match rates do not follow the usual FMAP formula, I exclude it from my analysis. I also exclude Arizona for the years 1985-1990 due to lack of beneficiary data. In total, my sample contains 1,415 state-year observations. Table 1 contains summary statistics for my analysis sample. Over my sample period, the average match rate was 62 percent and the average expenditure per

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\(^6\)The 2011-2013 MACStats data measure the number of enrollees. See Appendix Section A for details.
beneficiary (the main outcome) was about $7,656, though states varied widely in this dimension.

Since RKD identifies the causal effect for states whose relative PCPI is close to the kink point, I also present these statistics at the threshold. To do this, I regress each variable on cubic functions of the relative per-capita personal income (the running variable), where the functions differ on both sides of the threshold. The estimated intercept term above the threshold is reported in column (3) of Table 1. States near the threshold, as expected, have lower match rates—52 percent—and slightly lower spending per beneficiary. In terms of other state characteristics, states near the threshold are relatively higher educated, have lower poverty rates, have a lower proportion of elderly residents, and are larger in population size.

5 Empirical Results

5.1 Graphical Analysis

First, it is informative to plot match rates and outcome variables as a function of relative state per-capita personal income in order to visually gauge the size of the kinks. Figure 1 shows the first stage relationship between federal shares (match rates) and state PCPI. As one can clearly see, the formula accurately describes the actual federal share of Medicaid spending for the most part. As discussed in Section 2, there are some positive deviations from the match rate formula over the years, including the periods 2003-2004 and during the Great Recession. In each of the outcome plots, I split the range of the running variable (relative state PCPI) into 32 equal sized nonoverlapping bins, with 16 bins on each side of the threshold, and plot the mean values of each outcome variable (the bin containing 0 is the one just to the right of the threshold). Figure 2 shows the reduced form relationship between per-beneficiary spending on Medicaid and PCPI. There appears to be a kink in spending moving from one side of the threshold to the other.

While Figure 2 indicates that a higher match rate increases total (combined federal and state) spending on Medicaid, it does not show whether state spending on Medicaid has increased or decreased as a result. Indeed, it is possible that states can respond by increasing their own portion of expenditures, resulting in what Adams and Wade (2001) describe as a “stimulative” effect of a matching grant. On the other hand, states can capture some of the increased matching by lowering their own spending on Medicaid in such a way that combined federal and state spending is still higher on net.

An additional, more subtle implication is that just by estimating a response in the state’s own portion of Medicaid spending informs whether states view Medicaid as a substitute or complement to other budget
categories. Consider the case where states have fixed budgets. If state spending on Medicaid increases, then spending in other areas goes down; that is, states substitute some portion of spending on other goods towards Medicaid. On the other hand, if states respond by reducing their Medicaid expenditures and increasing other (non-Medicaid) spending, it implies that Medicaid and non-Medicaid budget categories are complementary.\(^7\)

There are theoretical arguments and suggestive evidence, for example, that Medicaid and cash assistance programs may be treated as substitutes in past decades (Moffitt, 1990; Baicker, 2001; Marton and Wildasin, 2007).

In Figure 3, the expenditures per beneficiary are disaggregated between that paid by the federal and state governments. While the federal government expenditures exhibit a pronounced kink at the threshold, spending on Medicaid from the state’s own sources appears not to change discontinuously with the match rate. These plots suggest that increases in the match rate only affect the federal portion of the expenditures. That is, the federal government bears the entirety of the increase in expenditures from increasing match rates. As noted above, the lack of response in the state’s own Medicaid expenditures is indicative that Medicaid is viewed neither as a complement nor a substitute to other categories of state spending.

Finally, a major appeal of RKD is the testability of its key assumption that state-years that are near the kink threshold are comparable on all dimensions other than the federal match rate. One standard validity test of an RKD is to check whether there are kinks in the distribution of observations over the running variable, relative PCPI. In Appendix Figure A.1, I split the range of the running variable into 32 bins and plot the number of observations in each bin. This confirms that states do not strategically choose their per-capita income to fall on one side of the threshold in order to secure a higher match rate, which seems unlikely in any case. A second, perhaps more realistic possibility is that while states do not strategically locate on one side of the threshold, it just so happens that states on either side differ in their characteristics. The second validity test therefore checks that observable state characteristics evolve smoothly over the kink threshold. To show this visually, I regress the main outcome measure, Medicaid expenditures per beneficiary, on a number of state characteristics, and use the prediction from the regression to form an index. The binned value of this index is plotted in Appendix Figure A.2. Characteristics include: the state’s average age, percent of the population under age 18, over 64, with at least a high school education, female, and in

\(^7\)To see this formally, suppose that the state’s budget constraint is given by \((1 - \theta)b(\theta) + x(\theta) = W\), where \(b(\cdot)\) and \(x(\cdot)\) are Medicaid and non-Medicaid spending, respectively, \(\theta\) is the Medicaid match rate, and \(W\) is a fixed state budget. This implies \(\frac{d(1 - \theta)b(\theta)}{d\theta} = -\frac{dx(\theta)}{d\theta}\), so that a positive response in the state’s share of Medicaid implies a positive cross-price elasticity for non-Medicaid spending, and vice versa.
poverty, the unemployment rate, and the population size. This index of covariates appear to evolve smoothly, allaying concerns of differences across the threshold. The next section shows more formal tests of covariate differences.

5.2 Main Elasticity Estimates

Table 2 reports the first stage estimates of the change in slope in the federal share percentage across the threshold and the RKD estimates of the effect of an increase the match rate on measures of Medicaid spending. For the first stage and each outcome presented in the column heading, I estimate a linear and a quadratic specification on the full sample as well as samples restricting to observations whose relative PCPI are within 0.3, 0.2, and 0.1 from the kink point.\(^8\)

The first column of Table 2 shows the estimated slope change as we move from the right of the threshold to the left, using various specifications. From the FMAP formula, the true first stage relationship is quadratic and the statutory slope change is -90 at the threshold. Examining the estimated first stage coefficients from quadratic specifications, however, bandwidths of less than 0.3 yield estimates that are quite far off—using a bandwidth of 0.2 rules out a slope change of -90 with a 95 percent confidence interval. Since Figure 1 shows that the relationship between the federal match and the relative per-capita income mostly follows the formula, this suggests that these bandwidths may be too small and contain too few observations to reliably deliver sensible estimates. Therefore, while I show how estimates vary with specification, the main estimates correspond to using those using a bandwidth of 0.3, which is the smallest bandwidth shown that still also yields a reasonable first stage relationship.

The second column of Table 2 shows the effect of a one percentage point increase in the match rate on my main outcome measure, per-beneficiary spending on Medicaid, for each sample and specification. In general, estimates grow more imprecise as I limit the sample closer to the kink point, which is to be expected as there are fewer observations. To better assess the tradeoff between sample size and the bias that may be introduced as I use points that are far from the threshold, I plot the point estimates and the 95 percent confidence interval for the RKD effect as a function of the bandwidth used for estimation. Appendix Figure A.3 shows the results of this exercise for the both linear and quadratic specifications. For both specifications, estimates are generally not stable and have large standard errors for bandwidths smaller than

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\(^8\)These cutoffs correspond to state PCPIs that are between 75 to 135 percent, 85 to 125 percent, and 95 to 115 percent of the national PCPI, respectively. All observations are within 65 to 145 percent of the national PCPI (which corresponds to a bandwidth of 0.4).
0.15, indicating again that estimates with smaller bandwidths are less reliable. Comparing the quadratic and linear specifications, estimates from a quadratic specification tend to be larger than those from a linear specification (and have substantially larger standard errors), though the estimates are close to agreement around a bandwidth of 0.3. Using the method proposed by Pei et al. (2020) to estimate the asymptotic mean-squared error of linear and quadratic specifications for each bandwidth, I find in Appendix Table A.1, column 1 that a linear specification minimizes this error for bandwidths of 0.2 and 0.3, while a quadratic specification is preferred with a bandwidth of 0.4. Taken together, I focus on the estimates from linear specifications with a 0.3 bandwidth, though I note that the linear specification with a 0.2 bandwidth yields similar results with somewhat larger standard errors.

The preferred specification indicates that a percentage point increase in the match rate increases per-beneficiary Medicaid spending by $210. To interpret this as an elasticity, note from Table 1 that the per-beneficiary spending at the threshold is $6830, implying an elasticity of spending with respect to the match rate of 1.6 or a price elasticity of -1.5. This estimate is much larger than the price elasticity estimate of -0.09 in Adams and Wade (2001), which may be downward biased, as discussed above. This estimate is also larger than most price elasticities found in the AFDC literature, particularly those that address endogeneity concerns between the match rates, state income, and welfare spending.

Although I find that per-beneficiary spending is responsive to match rates, a natural question is whether states also respond by changing eligibility requirements or outreach activities to increase the number of beneficiaries. I show these results in the next two columns of Table 2 by examining the spending per person in poverty (spending “per poor”) and the number of beneficiaries per person in poverty (beneficiaries “per poor”). I find no statistically significant response in the number of beneficiaries, with linear specifications pointing to less than a percent change in the number of beneficiaries per match rate percentage increase. Since states increase spending but do not respond by changing the number of Medicaid enrollees, this suggests that a focus on per-beneficiary spending will be sufficient for capturing the full response to match rates.

Next, Table 3 reports the RKD estimates corresponding to Figure 3, in which the expenditures are broken

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9The vertical dashed lines in this graph denote optimal bandwidths calculated following Calonico et al. (2014), using the associated Stata package rdrobust.

10Relying on older estimates, Chernick (2000) suggests that one reason why AFDC is less responsive to match rates is the interaction and substitution with food stamps. Since food benefits are a declining function of cash benefits, the Food Stamp Program imposes an implicit price on cash benefits that may exert more influence than AFDC match rates. Since food stamp benefits do not decline with Medicaid benefits, this interaction is not relevant for Medicaid.
down by state and federal sources. Again, estimates are reported for linear and quadratic specifications and for four bandwidths. The estimates confirm the visual evidence that the federal spending is driving the spending response. Using the preferred linear specification with a 0.3 bandwidth, I find that a percentage point increase in the match rate increases federal spending by $169, while state spending increases by less than $41 (statistically insignificant). A 95 percent confidence interval easily rules out the response found in Adams and Wade (2001) of a 162 percent reduction in state spending per percentage point increase in the match rate for an earlier period. The lack of a negative state spending response is consistent across specifications.

As noted above, the state spending response to match rates is informative of whether Medicaid is viewed as a substitute or complement for non-Medicaid spending in the case of fixed state budgets. While some studies suggest that Medicaid and cash assistance may be treated as substitutes (see, e.g., Moffitt, 1990; Baicker, 2001), which would imply a positive state spending response, I find little evidence that this is the case. Although the literature does not directly provide a benchmark magnitude for comparison, I find no larger than a 4 percent increase in state Medicaid spending per percentage point increase in the match rate (95 percent confidence interval), and cannot rule out a zero effect. This suggests that for the more recent period of the study, which covers the post-welfare reform era, Medicaid is not treated as a substitute for other spending categories.

For robustness, I show in Appendix Table A.2 that estimates are largely unchanged, particularly for larger bandwidths, when I include year fixed effects and observable state characteristics in the estimating equations. I show this for two reasons. First, as noted above in Section 4 and detailed in Appendix Section A, there were several changes over the years in how the number of beneficiaries were counted that may have resulted in uniform shifts in certain years. Second, although the composite covariate index shown in Appendix Figure A.2 does not exhibit any differences in states across the threshold, I show in Appendix Table A.3 that individual covariates may have statistically significant kinks when using my preferred specification (local linear regression with a bandwidth of 0.3). In particular, I find that there may be a decrease in the slope of percent female, elderly, and in poverty moving from the right of the threshold to the left, and possibly a marginally statistically significant increase in the slope for percent with a high school diploma. The final column of Appendix Table A.3, however, confirms the visual evidence that the kink in the predicted Medicaid spending per beneficiary, where the prediction uses linear terms of each covariate, is not statistically significant. This indicates that although each individual covariate may sometimes vary non-smoothly
over the threshold, it is likely not driving the measured kink in the Medicaid spending. Indeed, taken at face value, the point estimate of the kink in the predicted Medicaid spending actually goes in the “wrong” direction of finding a negative match rate response.\(^\text{11}\)

### 5.3 Mechanisms

Although the analysis presented so far suggests that Medicaid expenditures are responsive to federal match rates, it does not shed much light on the margins through which spending adjusts. The lack of responsiveness in the number of beneficiaries (Table 2) suggests that eligibility or outreach efforts are not likely to be driving the spending response. In this section, I explore other potential channels by examining disaggregated categories of spending.

The upper part of Table 4 explores which types of Medicaid services appear to be most responsive to the Medicaid match rate. Each row of this table shows the estimated effect of an increased match rate on different major categories of spending, as reported on the Financial Management Reports, where each estimate is obtained using a local linear specification with a 0.3 bandwidth (the first row is reproduced from Table 2).\(^\text{12}\) The second column shows the spending on that category per Medicaid beneficiary for states near the threshold (by estimating the intercept term similar to column 3 of Table 1). The largest spending categories are in hospitals and institutional long-term care, and responses to the match rate in these categories appear to be driving much of the total spending response. This pattern of findings suggests that states are not adjusting managed care spending, physician reimbursement rates associated with acute care, or prescription drug spending substantially in response to match rates.

The result that hospital and institutional long-term care spending is most responsive to the match rate is interesting in light of the study by Baicker and Staiger (2005), which shows that states may use fiscal schemes involving public hospitals to maximize federal matching funds. In particular, states may make supplemental payments to providers that are not tied to specific medical services, which qualify for a federal match, but are then reimbursed through provider taxes or local-to-state intergovernmental grants (see Coughlin et al., 2000 and MACPAC, 2017 for details).\(^\text{13}\) As a result, the reported state share of spending in

\(^{11}\)Using a local linear specification with a bandwidth of 0.3, a percentage point increase in the match rate decreases predicted Medicaid spending by $36 (not statistically significant).

\(^{12}\)See Appendix Section A for details on the expenditure categories that comprise each group.

\(^{13}\)The majority of supplemental payments to hospitals are Disproportionate Share Hospital (DSH) payments and Upper Payment Limit (UPL) payments (MACPAC, 2020b). DSH payments provide hospitals that serve a large share of the Medicaid or uninsured population with additional funds. UPL payments are lump-sum transfers to providers that are intended to make up the difference in cost of care between what Medicaid pays for services and the cost of providing these services according to Medicare.
the Financial Management Reports – which includes these payments – may be higher than the “true” level of medical care spending. To the extent that this “Medicaid maximization” behavior increases with match rates, the analysis above may also overstate the responsiveness of true medical spending to the match rate.

I conduct two exercises to explore whether the responsiveness to the match rate is driven primarily by “Medicaid maximization”. First, since supplemental payments through the DSH program do not necessarily mean that states provide more services, I show the effects of the match rate on hospital and long-term care spending net of DSH payments in Panel A of Table 4 for 1993 onward, which is when the breakdown is reported in the FMR data. This exercise suggests that for long-term care institutions, almost the entire effect of the match rate on spending is due to non-DSH payments. For hospitals, the impact of the match rate is weaker when we do not consider DSH payments, dropping from a $81 to a $46 increase per percentage point increase in the match rate, but it is still statistically significant and substantial. In Panel B of Table 4, I confirm these effects using data from the Medicaid Statistical Information System, which reports Medicaid payments as well as number of people who received services from each category. One of the main differences between MSIS payment data and the FMR is that MSIS—which is used primarily for statistical purposes rather than for administering the program—does not contain supplemental payments like DSH. When I break down the two categories to explore whether there were increases in the number of people served, I find that for hospitals, there was about a 2 percent increase in the number of people who received hospital services but no statistically significant effect on the payments per person served. On the other hand, when I examine long-term institutional care spending, the effect of the match rate seems to be coming through the payment per person served, rather than the number of individuals using the services. This is consistent with a finding in Grannemann and Pauly (1983) who note that reimbursement rates, rather than the number of service recipients, in institutional care was a primary driver of the growth in Medicaid spending in the late 1970s.

In a second exercise, I adjust spending levels directly by accounting for payments that are sent back to state governments via provider taxes and intergovernmental transfers.\footnote{I focus on provider taxes and intergovernmental transfers because these are the main non-general-fund sources that states use to fund their Medicaid share (GAO, 2014). The analysis in Adams and Wade (2001), focusing on the 1984-1992 period, subtracts “provider taxes and donations” (obtained through survey data) from state revenues.} Although there is no direct way to see this in the data, the closest available proxies are available in a survey conducted by the Government Accountability Office (GAO), which covers the fiscal years 2008 to 2012 and contains information about sources and amounts of Medicaid funding (from e.g., general funds, local governments, provider taxes).
Since this data is only limited to four years of my study period, I combine it with information from the Census’s Annual Survey of State and Local Government Finances, which reports detailed sources and amounts of state government revenue, to extrapolate to other years in my data. While the state government revenue data do not specifically indicate that certain revenue sources are for financing Medicaid, I show that two categories likely contain these payments: “local intergovernmental support for public welfare” and “other selective sales and gross receipts taxes”. Over the four years that the GAO study covers, I find that a regression of “local intergovernmental support for public welfare” on intergovernmental sources of Medicaid funding yields a highly statistically significant coefficient of 0.56 (s.e. 0.01). Although “other selective sales and gross receipts taxes” likely includes provider as well as other taxes, a simple regression on provider taxes used for Medicaid funding yields a statistically significant coefficient of 0.62 (s.e. 0.15). I use these estimated coefficients to extrapolate that 56 percent and 62 percent of revenues from “local intergovernmental support for public welfare” and “other selective sales and gross receipts taxes”, respectively, are used for Medicaid financing in the other years of my data. I then subtract these amounts from the the state share of payments.

Appendix Table A.4 shows the estimated effects of the federal match on this adjusted Medicaid spending (using the benchmark local linear specification with a bandwidth of 0.3). Compared with Tables 2 and 3, this adjustment alters estimates slightly (the effects on the federal share are exactly the same as there were no adjustments made). In particular, increased match rates do not appear to incentivize states to rely more heavily on financing arrangements that maximize federal funding and reduce the state share. Combined with the results of Table 4, this suggests that match rates do seem to increase Medicaid spending, particularly on hospitals and long-term institutional care.

5.4 Alternative Empirical Strategy and Results

As discussed above, since the Medicaid match rate formula for most categories of spending has been unchanged since the program’s inception (except for fiscal relief during downturns), there is limited useful variation for estimating match rate effects. Apart from the kink induced by the match rate floor that was explored above, one other source of variation in the match rate is driven by updates to per-capita personal income calculations. Therefore as an alternative identification strategy, I utilize within-state changes in the match rate that are likely driven by methodological changes in calculating per-capita personal income.

In Appendix Section B, I show that yearly changes in a state’s match rate can be attributed to a compo-
nent that is associated with incorporating a new year of per-capita personal income measures and a component that is due to an update of prior years’ estimates of per-capita personal income. The latter may be large if there are major changes in how personal income is calculated, such as during “comprehensive revisions” that occur every five years or so, or when there is a significant update to population counts, such as after the Decennial Census. I identify years in which states experience these large updates in the prior year’s PCPI estimates, which are likely due to methodological changes, and present a series of event study analyses in the five years around each PCPI “shock.”

I find strong first stage relationships between positive or negative PCPI revisions and the federal match. The match rates exhibit statistically significant changes in the correct direction that persist for several years after these PCPI revisions. However, when I examine Medicaid spending per beneficiary around the same PCPI shock, I do not find effects that are statistically distinguishable from zero (see Appendix Section B for details). While this may seem to contradict the findings of the previous subsections, I note that the estimate is actually quite imprecise and a 95 percent confidence interval does not rule out the magnitudes found using an RKD. It is also possible that this alternative methodology isolates changes in match rates that are too small to be meaningful enough for a state to change their behavior. Therefore, the main empirical strategy used in this study that relies on the kinked match rate formula may be the only viable way to gain traction on this important policy question.

6 Welfare Effects of Medicaid Financing Reform

In this section, I turn to the normative implications of the estimated spending elasticity. Specifically, I present a simple framework that justifies the use of matching grants and consider how a reduction in the match rate (i.e., a switch to block grant financing) may impact social welfare. The starting point of the model is the assumption that states, which are heterogeneous and “closer” to the people than the federal government, should be responsible for redistribution policies like Medicaid (Pauly, 1973). However, decentralized redistribution policies may generate spillovers across states, warranting federal subsidies in the form of matching grants. In addition to their “corrective” role, the matching grants in the model also aid in the federal government’s cross-state equity goals, motivated by the fact that Medicaid grants are currently structured so that states with lower per-capita income have higher matches.
6.1 Model

In this model, each state government—whose preferences might be determined by the state’s median voter—chooses how much to spend on its own Medicaid program (per beneficiary) \( B_i \) and on other policy areas \( X_i \) to maximize a state-specific utility function subject to an exogenous budget constraint. In addition to the positive value it places on its own Medicaid spending, the state also values national Medicaid generosity \( \bar{B} \), which it takes as given. This might be due to mobility, since states with higher relative Medicaid spending may attract larger poor populations, as in classic models of decentralized redistribution (Gramlich and Laren, 1984; Brown and Oates, 1987; Wildasin, 1991). However, since interstate mobility does not appear to drive Medicaid spending patterns in recent years (Baicker et al., 2012), another motivation for this preference structure is simply that residents of a state are altruistic towards poor residents who live in the same state as well as the national poor.

Formally, each state \( i \) solves the following problem:

\[
\max_{B_i, X_i} U_i(B_i, \bar{B}) + X_i
\]

such that

\[
X_i + (1 - \theta_i)P_iB_i = W_i - \tau_i
\]

where \( \theta_i \) is the Medicaid match rate, \( P_i \) is the number of Medicaid beneficiaries in the state, \( W_i \) is an exogenous state budget, and \( \tau_i \) is a lump-sum tax to the federal government used to fund the Medicaid grants. There are three aspects of the problem worth noting. First, because of the quasi-linear form of the state’s utility function, there are no income effects of Medicaid spending. This may approximate reality if income effects are small, though I discuss how allowing for income effects changes the analysis in the Appendix. Second, I assume for simplicity that the number of Medicaid beneficiaries \( P_i \) is not a choice variable for the state, which matches the empirical finding that the number of beneficiaries does not change in response to the match rate. However, it is possible to endogenize the number of beneficiaries \( P_i \) by incorporating it into the utility of the state.\(^{15}\) Finally, although taxes are assumed to be lump-sum to abstract away from tax distortion issues, there may be additional costs to raising revenue in reality that are not captured in the model.

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\(^{15}\) One way to do this that minimally affects the problem would be to redefine \( B_i \) as the total Medicaid spending in state \( i \). The budget constraint would be \( X_i + (1 - \theta_i)B_i = W_i - \tau_i \) in this case.
The state’s first order condition is
\[ \frac{U_i}{P_i} = 1 - \theta_i \] (2)
where \( U_{ij} \) denotes the partial derivative of \( U_i \) with respect to the \( j \)th argument. Without matching (\( \theta_i = 0 \)), states will choose spending such that the marginal utility of own-state Medicaid spending per beneficiary equals the marginal utility of spending on other policies (which is equal to 1).

Now consider the social planner’s problem. Following the optimal taxation literature, I assume that the planner maximizes a weighted sum of individual states’ utilities. The weights represent a desire to redistribute funds across states, which may be justified by unequal resources and tax bases. Indeed, the reason that the current match rate formula depends on per-capita income is that it proxies for a state’s ability to pay for benefits (GAO, 1990). If social weight \( g_i \) is placed on state \( i \), optimal spending allocations will be the solution to
\[
\max_{\{B, X\}_{i=1}^S} \sum_{i=1}^S g_i \left[ U_i(B_i, \bar{B}) + X_i \right]
\]
such that \( \sum_{i=1}^S X_i + \sum_{i=1}^S P_i B_i = \sum_{i=1}^S W_i \), where \( S \) equals the number of states. Noting that \( \bar{B} = \sum_{i=1}^S P_i B_i / \sum_{i=1}^S P_i \), optimality requires that
\[
\frac{U_i}{P_i} + \sum_{j=1}^S \frac{g_j U_j}{g_i \sum_{j=1}^S P_j} = 1
\] (3)
This means that states will underprovide benefits in a decentralized setting relative to the optimum in the absence of federal matching (\( \theta_i = 0 \)). The extent of the underprovision is determined by the value all states place on state \( i \)’s Medicaid spending, relative to the weight on state \( i \)’s utility.

Suppose that the federal government can match state spending on Medicaid and finance grants by lump-sum taxes. The federal government selects match rates by solving:
\[
\max \left\{ \theta_i \right\}_{i=1}^S \sum_{i=1}^S g_i \left[ U_i(B_i, \bar{B}) + W_i - (1 - \theta_i) P_i B_i - \tau_i \right]
\]
such that the budget balances
\[
\sum_{i=1}^S \theta_i P_i B_i = \sum_{i=1}^S \tau_i
\]
Note that the budget balance requirement implies that any change in outlays resulting from an increased match rate \( \theta_i \) must be funded by an increase in lump sum taxes such that \( \sum_{j=1}^S d\tau_j / d\theta_i = d(\theta_i P_i B_i) / d\theta_i \). For simplicity, I will show the resulting optimal match rate when all states share the increased tax burden equally, \( d\tau_j / d\theta_i = d\tau_k / d\theta_i \).
for all \( j \neq k \). While this simplification will affect the exact expression of optimal match rate, it ultimately will not affect the exercise of comparing the social welfare under different financing regimes. As discussed in the Appendix, this is because in the calibration exercise below, social welfare weights will only be identified up to a normalization, and assumptions about how the tax burden is distributed will affect only that normalization. The optimal match for state \( i \) is given by

\[
\theta_i = \frac{\sum_{j=1}^{S} g_j U_j^2}{\bar{g} \sum_{j=1}^{S} P_j} \cdot \frac{\varepsilon_i}{1 + \varepsilon_i - \frac{\bar{g}}{\bar{g}}}
\]

where \( \varepsilon_i \equiv \frac{dB_i}{d\theta_i} \) is the elasticity of Medicaid spending with respect to the match rate and \( \bar{g} \equiv \frac{1}{S} \sum_{i=1}^{S} g_i \) is the average of the social weights (see Appendix Section C for details). Note that if all states are given equal weight \( g_i \), the optimal match rate is equal to the spillover state \( i \) generates in its choice of Medicaid spending and the first-best allocation (3) will be achieved, as pointed out by Wildasin (1991) in a similar setting. In general, with different social weights and taxes that allow for cross-state subsidization, matching grants function both to correct the externalities imposed by states’ spending decisions as well as to redistribute funds across states.\(^{16}\) The latter role of the match rate can be seen in the second multiplicative factor of (4), which increases with social weight \( g_i \).

### 6.2 A Medicaid Financing Reform

I now discuss the implications of this model for Medicaid financing reform by considering a general reform that changes match rates from \( \theta^* \) to \( \theta \). As mentioned in the introduction, one possible reform is a switch from matching grants to block grants, which effectively reduces match rates to zero for all states. If Medicaid spending in state \( i \) under match rate \( \theta_i^* \) is given by \( B_i^* \), national Medicaid spending \( \bar{B}^* \), and the lump-sum tax required to fund the system \( \tau_i^* \), total social welfare under matching regime \( \theta^* \) is

\[
\sum_{i=1}^{S} g_i [U_i(B_i^*, \bar{B}^*) + W_i - (1 - \theta_i^*) P_i B_i^* - \tau_i^*]
\]

\(^{16}\)If the lump-sum taxes are set to equal the matching grant amount (\( \tau_i = \theta_i P_i B_i \) for all \( i \)) so that there is no scope for redistribution across states, the optimal match rate will achieve the first-best allocation. However, the optimal match rate in this case will not have the realistic property that states with higher social weights have larger matches.
while total social welfare under the reformed regime $\theta$ is

$$
\sum_{i=1}^{S} g_i [U_i(B_i, \bar{B}) + W_i - (1 - \theta_i)P_i B_i - \tau_i]
$$

As shown in Appendix Section C, the change in social welfare, after normalizing by the average welfare weight $\bar{g}$, can be approximated by

$$
\sum_{i=1}^{S} \frac{g_i}{\bar{g}} \left[ (\theta_i - \theta^*_i)P_i B_i^* - (\tau_i - \tau^*_i) \right] + (\bar{B} - \bar{B}^*) \frac{\sum_{i=1}^{S} g_i U_i^2}{\bar{g}}
$$

(5)

The first term represents the social value of the mechanical changes in each state’s net transfer, which I call the “equity term”. The second term represents the welfare effects associated with the change in national Medicaid spending, which I will refer to as the “externality term”. Therefore, depending on the structure of the reform, it is possible for a reduction in match rates – which will reduce Medicaid spending – to be welfare-enhancing if it has sufficient cross-state redistributive value.

**Calibration of Welfare Weights**

An estimate of the welfare change of any given reform requires information on the relative weights $g_i$ placed on each state’s utility and the value of national Medicaid spending to the federation (i.e., the externality term). Since there are no empirical measures of these welfare quantities, I calibrate them by adapting an “inverse-optimum” approach that is used to infer social welfare weights from tax policies (e.g., Bourguignon and Spadaro, 2012; Gordon and Cullen, 2012; Lockwood and Weinzierl, 2016). Specifically, this approach assumes the existing Medicaid matching system is optimal and calculates the social welfare weights and valuation of Medicaid spending that rationalizes the current match rates.

To do this, recall that the socially optimal Medicaid match rate is

$$
\theta_i = \frac{\sum_{j=1}^{S} g_j U_j^2}{\bar{g} \sum_{j=1}^{S} P_j} \cdot \frac{\varepsilon_i}{1 + \varepsilon_i - \frac{\bar{w}}{\bar{g}}}
$$

and the objective is to infer the quantities $\sum_{i=1}^{S} g_i U_i^2 / \bar{g}$ and $\bar{w} / \bar{g}$. I proceed in two steps. First, I rely on the observation that the match rate minimum is 50 percent for high-income states. If this match rate reflects the optimal match to correct the externality from state spending without any redistributive objectives, a
reasonable assumption may be that $\frac{\sum g_i U_j}{\sum \bar{g}_j P_j} = 0.5$. One way to see this is to consider a federation consisting only of states at the floor match rate. In this hypothetical federation, it might be reasonable to assume all states have identical social welfare weights (and that there is no redistributive function of matching grants), but that there are still spillovers to Medicaid spending that justifies the matching. Since $\bar{g}_j = 1$ in this hypothetical federation, the term labeled (B) is equal to 1, and the optimal match rate is given by (A). In the second step, I use the fact that lower income states have match rates above 50 percent. With my estimate of match rate elasticity $\varepsilon_i$ (assuming that it is constant across states) and $\sum g_i U_j \bar{g}_j \sum S_j P_j = 0.5$, I can infer the weights $\bar{g}_j$ for each state using its actual match rate. The results of this exercise suggest that the weight placed on Mississippi with a match rate of 74 percent in 2013 is weighted approximately 1.5 times more than a state at the 50 percent floor match rate (e.g., Massachusetts).

While this calibration depends on the assumption that current match rates are optimally set by policymakers, it may be a reasonable starting point for a welfare analysis. In particular, the weights $\bar{g}_j$, which are obtained by comparing match rates between high- and low-income states, may approximately reflect the relative social weights, even if the 50 percent floor match rate is not indicative of the spillover benefits of Medicaid. In the policy simulations below, I therefore also examine how the welfare calculation changes when I use alternative (smaller) externality valuations $\sum g_i U_j \bar{g}_j \sum S_j P_j$.

### Block Grant Simulation Results

I now calibrate expression (5) to understand the welfare implications of a switch to block grant financing, which effectively reduces match rates to zero for all states. I consider two potential block grant structures. The first is a simple conversion of each state’s matching grant into a block grant, where the federal government transfers the dollar value of the existing matching grant to the state but does not adjust the size of the grant when states spend more or less on Medicaid. Since the value of the existing matching grant is determined by current state spending choices, grants tend to be larger for higher income states even if they have low match rates. Therefore, I also consider a second block grant structure that reallocates grants based on population size and per-capita income, following Clemens and Ippolito (2018).

\[17\] Indeed, if one considers the history of the Medicaid program, it seems unlikely that the 50 percent floor match rate was designed to optimally offset perceived state spillovers. First, Medicaid was considered a last-minute “afterthought” to the 1965 law that created Medicare (Rose, 2013). Second, the generous floor match rate was initially thought to be necessary to induce historically reluctant states to participate, though ultimately states turned out to be fairly enthusiastic about expanding the program. On the other hand, the dependence of the match rate on state personal income does appear to be due to a desire to redistribute funds to states that have smaller fiscal capacities and higher poverty rates (GAO, 1990).
In both cases, a conversion from matching to block grant financing will reduce the amount each state chooses to spend on Medicaid, making the second term in (5) negative. The first term, which is determined by the mechanical change in transfers will be zero by definition for a reform that simply converts the existing matching grant into a block grant.\footnote{To conserve on and slightly abuse notation, I now assume that lump sum taxes $\tau_i$ incorporate the block grant amounts.} A reform that reallocates transfers towards lower-income states, however, may result in a positive contribution to the first term of (5), even if the total dollar amount of transfers remains the same. For both types of reform, I consider how much larger the block grants must be to maintain the status quo level of welfare under matching grants (with negative values indicating that a reduction in grant spending can achieve the same level of welfare as existing matching grants).

I use the match rates and spending in the last year of my data (2013), excluding Alaska. I calculate the predicted change in national Medicaid spending $\bar{B} - \bar{B}^*$ using estimates obtained in Section 5. My preferred estimate of a $210 reduction in per-beneficiary spending per match rate percentage point implies that state Medicaid spending would be reduced substantially, often to zero. I therefore also impose a minimum spending level equal to the state’s share of spending per beneficiary, assuming that any block grant reform would be accompanied by a “maintenance of effort” provision that requires states to spend at least the amount they did on Medicaid pre-reform.\footnote{Although proposals do not typically contain details such as maintenance of effort provisions, this level is consistent with the 2003 proposal under President Bush (Lambrew, 2005).} I find that the change in national per-beneficiary spending on Medicaid would be reduced by $823 per beneficiary, or 57 percent.

Putting together the calibrated social welfare weights and the implied reduction in national Medicaid spending in expression (5), I find that if we simply convert existing matching grants into block grants maintaining the 2013 distribution of funding across states, block grants would need to be 41 percent larger than matching grants to achieve the same welfare level. I also consider a second reform similar to one proposed by Clemens and Ippolito (2018) that reallocates funding such that the block grant for state $s$ is proportional to $\frac{PCPI_{US}}{PCPI_s} \cdot Pop_s$, where $PCPI_{US}$ and $PCPI_s$ are the national and state $s$ per-capita personal incomes over the most recent three years, respectively, and $Pop_s$ is the population in state $s$. Even at the same level of total funding, this reform is strongly redistributive across states, increasing some states’ allocations by up to 107 percent and reducing others by 54 percent. Since this reallocation generates positive social value, the required increase in block grant funding to achieve the same level of welfare as matching grants is reduced to 39 percent.

Finally, as mentioned above, the estimates presented in the previous paragraph depend on the assumption...
that current match rates reflect society’s valuation of Medicaid spending. In particular, the externality value is pinned down by the minimum match rate of 50 percent. However, it is possible that the 50 percent match rate reflects a simple “fair” split of costs between federal and state governments and the actual externality value is lower than implied by current match rates. Therefore, in Figure 4, I present the welfare results under alternative assumptions about the externality value of Medicaid (while keeping the social weights on individual states the same as before). The solid line shows, for externality valuations ranging from zero to a value that implies a 50 percent floor match, how much block grants need to exceed existing allocations to maintain the level of welfare achieved by matching grants. The dashed line shows the equivalent exercise for the reallocative grants described above, where block grants are proportional to a state’s relative per-capita income and population. In both cases, the size of the block grants increases with the assumed externality value of Medicaid, as expected. With reallocative block grants, the required increase is slightly lower due to the offsetting welfare effects of redistributing grants to states with higher social weights. For very low social valuations of the Medicaid externality, the reallocative block grants could even produce positive social value.

7 Conclusion

This paper explores the causal effect of an increase in the federal match rate on Medicaid spending by exploiting the quasi-experimental variation created by a kink in the match rate formula. Previous studies that attempt to measure price effects of means-tested programs are plagued by the fact that match rates are linked to state incomes. Using the RKD methodology formalized by Card et al. (2015), I find that a one percentage point increase in the match rate increases expenditures per beneficiary by $210, or about 3 percent. By breaking down the expenditures by federal or state sources, I find that increases in match rates do not increase state expenditures on Medicaid, but overall spending does increase due to an increased federal contribution. Furthermore, I find that this increase is likely driven by increases in spending on hospitals and long-term care institutions.

To understand the welfare implications of this result, I present a model that rationalizes the current structure of Medicaid financing, in which the federal government aims to correct interstate spillovers from Medicaid spending and equalize resources across states. I show that the optimal match rate can be expressed as a function of social welfare weights, the social valuation of spillovers, and the spending elasticity. I then
simulate the welfare change associated with a block grant reform using my spending elasticity estimates and by assuming the current match structure reflects social preferences. I find that in order to maintain the current welfare levels, block grants should be set at 141 percent of the current Medicaid federal grant.

This analysis takes a first step in using the structure of Medicaid financing to evaluate the potential effects of reforms that change the marginal price of public health insurance. As mentioned in the introduction, the estimates in this study may also be informative for considering the effects of increasing match rates for certain populations or service categories, such as those enacted recently as a part of the ACA. Other reforms may include changing the match rate formula to depend on more than just the state’s per-capita income, or one that has varying match rates for different spending levels, as suggested by Grannemann and Pauly (1983). In order to evaluate these reforms, future work may consider expanding the welfare framework presented in this study to incorporate other policy objectives such as benefit equalization across states.
References


Notes: Sample includes all states 1985-2013 except AK for all years and AZ 1985-1990. The kink point, where state PCPI $= \sqrt{\frac{0.5}{0.45}} \cdot$ (national PCPI) is normalized to be at 0.
Figure 2: Medicaid Spending per Beneficiary vs. Relative PCPI

Notes: Sample includes all states 1985-2013 except AK for all years and AZ 1985-1990. Each point represents the mean expenditures per beneficiary for all observations falling within the bin of relative state PCPI. Bins are of width 0.025. The kink point, where state \( \text{PCPI} = \sqrt{0.5 \cdot \text{national PCPI}} \), (national PCPI) is normalized to be at 0, is denoted by the vertical line.
Figure 3: Medicaid Spending per Beneficiary vs. Relative PCPI - By Source
Panel A: Spending From Federal Sources

Panel B: Spending From State Sources

Notes: Sample includes all states 1985-2013 except AK for all years and AZ 1985-1990. Each point represents the mean expenditures per beneficiary from either federal or state sources for all observations falling within the bin of relative state PCPI. Bins are of width 0.025. The kink point, where state PCPI = \( \sqrt{0.5 \cdot 0.45} \) (national PCPI) is normalized to be at 0, is denoted by the vertical line.
Notes: This graph shows the simulated percent increase in each state’s block grant amount that is required to maintain welfare at the status quo level (under matching grants). The horizontal axis is a measure of the interstate spillovers associated with Medicaid spending, as implied by the optimal minimum match rate. “Current Allocation” simply converts state’s 2013 matching grant amounts into block grants, while “Need-Based Allocation” redistributes grants across states according state-income and population size. See text for details.
Table 1: Descriptive Statistics

<table>
<thead>
<tr>
<th></th>
<th>Mean (1)</th>
<th>SD (2)</th>
<th>Threshold (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Federal Match Percentage</td>
<td>62</td>
<td>9</td>
<td>52</td>
</tr>
<tr>
<td>Total Medicaid Spending (mil)</td>
<td>6292</td>
<td>8816</td>
<td>4194</td>
</tr>
<tr>
<td>Fed Share</td>
<td>3671</td>
<td>4731</td>
<td>2236</td>
</tr>
<tr>
<td>State Share</td>
<td>2621</td>
<td>4176</td>
<td>1958</td>
</tr>
<tr>
<td>Number of Beneficiaries (thou)</td>
<td>881</td>
<td>1329</td>
<td>1276</td>
</tr>
<tr>
<td>Medicaid Expenditures per Beneficiary</td>
<td>7656</td>
<td>2645</td>
<td>6830</td>
</tr>
<tr>
<td>Fed Share</td>
<td>4632</td>
<td>1311</td>
<td>3525</td>
</tr>
<tr>
<td>State Share</td>
<td>3024</td>
<td>1576</td>
<td>3305</td>
</tr>
<tr>
<td>Medicaid Expenditures per Poor</td>
<td>8685</td>
<td>4437</td>
<td>7696</td>
</tr>
<tr>
<td>Medicaid Beneficiaries per Poor</td>
<td>1.15</td>
<td>0.49</td>
<td>1.19</td>
</tr>
</tbody>
</table>

**Other State Characteristics**

<table>
<thead>
<tr>
<th></th>
<th>Mean (1)</th>
<th>SD (2)</th>
<th>Threshold (3)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Average Age</td>
<td>35.63</td>
<td>1.94</td>
<td>35.36</td>
</tr>
<tr>
<td>Percent Children</td>
<td>25.82</td>
<td>2.56</td>
<td>25.53</td>
</tr>
<tr>
<td>Percent Elderly</td>
<td>12.36</td>
<td>1.85</td>
<td>11.35</td>
</tr>
<tr>
<td>Percent with High School Diploma</td>
<td>78.33</td>
<td>5.58</td>
<td>80.56</td>
</tr>
<tr>
<td>Percent Female</td>
<td>51.06</td>
<td>0.97</td>
<td>50.42</td>
</tr>
<tr>
<td>Percent in Poverty</td>
<td>12.88</td>
<td>3.75</td>
<td>10.31</td>
</tr>
<tr>
<td>Annual Unemployment Rate (%)</td>
<td>5.74</td>
<td>1.93</td>
<td>5.83</td>
</tr>
<tr>
<td>Population Size (mil)</td>
<td>5.65</td>
<td>6.13</td>
<td>6.48</td>
</tr>
</tbody>
</table>

Notes: All monetary amounts are expressed in 2013 dollars. "per Poor" measures express spending and enrollees divided by the number of people in poverty. The total number of state-year observations is 1415.
Table 2: RKD Estimates of Match Rate Impacts on Medicaid Spending and Beneficiaries

<table>
<thead>
<tr>
<th>Bandwidth</th>
<th>Poly Order</th>
<th>First Stage</th>
<th>Expenditures</th>
<th>Expenditures</th>
<th>Beneficiaries</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>Per Beneficiary</td>
<td>Per Poor</td>
<td>Per Poor</td>
</tr>
<tr>
<td>0.4</td>
<td>p=1</td>
<td>-78.94</td>
<td>127.91</td>
<td>213.38</td>
<td>0.0011</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[1.44]</td>
<td>[55.18]</td>
<td>[94.96]</td>
<td>[0.0095]</td>
</tr>
<tr>
<td></td>
<td>p=2</td>
<td>-98.15</td>
<td>382.10</td>
<td>467.84</td>
<td>0.0029</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[5.06]</td>
<td>[135.58]</td>
<td>[270.79]</td>
<td>[0.0265]</td>
</tr>
<tr>
<td>0.3</td>
<td>p=1</td>
<td>-80.10</td>
<td>210.10</td>
<td>232.78</td>
<td>-0.0064</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[1.79]</td>
<td>[66.04]</td>
<td>[134.60]</td>
<td>[0.0125]</td>
</tr>
<tr>
<td></td>
<td>p=2</td>
<td>-99.98</td>
<td>270.01</td>
<td>625.94</td>
<td>0.0320</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[7.32]</td>
<td>[200.83]</td>
<td>[335.50]</td>
<td>[0.0310]</td>
</tr>
<tr>
<td>0.2</td>
<td>p=1</td>
<td>-87.54</td>
<td>256.07</td>
<td>408.63</td>
<td>0.0095</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[3.72]</td>
<td>[99.61]</td>
<td>[191.34]</td>
<td>[0.0172]</td>
</tr>
<tr>
<td></td>
<td>p=2</td>
<td>-58.54</td>
<td>902.17</td>
<td>842.65</td>
<td>-0.0184</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[13.03]</td>
<td>[548.32]</td>
<td>[911.06]</td>
<td>[0.0921]</td>
</tr>
<tr>
<td>0.1</td>
<td>p=1</td>
<td>-61.34</td>
<td>377.24</td>
<td>501.96</td>
<td>0.0015</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[6.33]</td>
<td>[258.69]</td>
<td>[543.80]</td>
<td>[0.0612]</td>
</tr>
<tr>
<td></td>
<td>p=2</td>
<td>-53.07</td>
<td>2708.21</td>
<td>2253.40</td>
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<tr>
<td></td>
<td></td>
<td>[43.00]</td>
<td>[2437.16]</td>
<td>[2734.76]</td>
<td>[0.2490]</td>
</tr>
</tbody>
</table>

Notes: Each cell in the column “First Stage” is an estimate of change the in slope in the federal match rate moving from the right to the left of the threshold, using different bandwidths and polynomial orders. Each cell for the subsequent columns represents an estimate of the effect of a percentage point increase in the federal match rate on the outcome denoted in the column heading for various specifications. "Poly Order" denotes the polynomial order. "Per Poor" measures express expenditures and beneficiaries divided by the number of people in poverty. Standard errors (in brackets) are clustered at the state level.
Table 3: RKD Estimates of Match Rate Impacts on Medicaid Spending: Federal and State Sources

<table>
<thead>
<tr>
<th>Bandwidth</th>
<th>Poly Order</th>
<th>Federal Share</th>
<th>State Share</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.4</td>
<td>p=1</td>
<td>124.79</td>
<td>3.11</td>
</tr>
<tr>
<td></td>
<td>p=2</td>
<td>[29.44]</td>
<td>[26.14]</td>
</tr>
<tr>
<td>0.3</td>
<td>p=1</td>
<td>169.28</td>
<td>40.81</td>
</tr>
<tr>
<td></td>
<td>p=2</td>
<td>[34.72]</td>
<td>[31.61]</td>
</tr>
<tr>
<td>0.2</td>
<td>p=1</td>
<td>196.43</td>
<td>59.64</td>
</tr>
<tr>
<td></td>
<td>p=2</td>
<td>[53.31]</td>
<td>[46.66]</td>
</tr>
<tr>
<td>0.1</td>
<td>p=1</td>
<td>260.94</td>
<td>116.30</td>
</tr>
<tr>
<td></td>
<td>p=2</td>
<td>[132.74]</td>
<td>[126.45]</td>
</tr>
<tr>
<td></td>
<td></td>
<td>[1280.76]</td>
<td>[1157.16]</td>
</tr>
</tbody>
</table>

Notes: Each cell represents an estimate of the impact of a percentage point increase in the federal match rate on federal or state spending per beneficiary, estimated using various specifications. "Poly Order" denotes the polynomial order. Standard errors (in brackets) are clustered at the state level.
Table 4: RKD Estimates of Match Rate Impacts on Medicaid Spending: Detailed Spending Categories

Panel A: Expenditures (FMR Data)

<table>
<thead>
<tr>
<th>Service Category</th>
<th>RK Estimate</th>
<th>Thrs Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total</td>
<td>210.10</td>
<td>6830.38</td>
</tr>
<tr>
<td></td>
<td>[66.04]</td>
<td></td>
</tr>
<tr>
<td>Hospital</td>
<td>81.04</td>
<td>1585.42</td>
</tr>
<tr>
<td></td>
<td>[22.06]</td>
<td></td>
</tr>
<tr>
<td>No DSH*</td>
<td>45.71</td>
<td>1180.67</td>
</tr>
<tr>
<td></td>
<td>[20.16]</td>
<td></td>
</tr>
<tr>
<td>Long-term (Inst)</td>
<td>97.01</td>
<td>2068.61</td>
</tr>
<tr>
<td></td>
<td>[47.57]</td>
<td></td>
</tr>
<tr>
<td>No DSH*</td>
<td>84.11</td>
<td>1317.20</td>
</tr>
<tr>
<td></td>
<td>[37.51]</td>
<td></td>
</tr>
<tr>
<td>Long-term (Non-inst)</td>
<td>11.26</td>
<td>765.66</td>
</tr>
<tr>
<td></td>
<td>[18.66]</td>
<td></td>
</tr>
<tr>
<td>Acute Care</td>
<td>6.35</td>
<td>1016.46</td>
</tr>
<tr>
<td></td>
<td>[17.12]</td>
<td></td>
</tr>
<tr>
<td>Drugs</td>
<td>13.82</td>
<td>406.62</td>
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<tr>
<td></td>
<td>[4.00]</td>
<td></td>
</tr>
<tr>
<td>Medicare</td>
<td>7.94</td>
<td>169.42</td>
</tr>
<tr>
<td></td>
<td>[3.93]</td>
<td></td>
</tr>
<tr>
<td>Managed Care</td>
<td>-7.32</td>
<td>818.27</td>
</tr>
<tr>
<td></td>
<td>[28.40]</td>
<td></td>
</tr>
</tbody>
</table>

Panel B: Service Expenditures and Service Recipients (MSIS Data)

<table>
<thead>
<tr>
<th>Service Category</th>
<th>Expenditures Per Beneficiary</th>
<th>Service Recipients Per Beneficiary (x1000)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>RK Estimate</td>
<td>Thrs Value</td>
</tr>
<tr>
<td>Hospital</td>
<td>41.34</td>
<td>1250.32</td>
</tr>
<tr>
<td></td>
<td>[17.93]</td>
<td></td>
</tr>
<tr>
<td>Long-term (Inst)</td>
<td>89.80</td>
<td>2007.88</td>
</tr>
<tr>
<td></td>
<td>[46.97]</td>
<td></td>
</tr>
</tbody>
</table>

Notes: In Panel A, the first column shows the impact of a percentage point increase in the federal match on the spending category denoted by the row heading, using a local linear specification with a bandwidth of 0.3. The second column shows the estimated spending at the threshold. The data sources for Panel A are Medicaid Financial Management Reports 1985-2013; categories labeled “No DSH” are only available after 1992. In Panel B, columns (1), (3), and (5) show the impact of a percentage point increase in the federal match on the outcomes denoted in the column headings, for the service denoted by the row headings. Columns (2), (4), and (6) show the estimated outcome at the threshold. The data sources for Panel B are the Medicaid Statistical Information System state summary tables, 1985-2011. Standard errors (in brackets) are clustered at the state level.
Appendix

A Data Appendix

A.1 Expenditure Data

The expenditure data used in this study are primarily from the annual Medicaid Financial Management Reports (FMR), which are derived from the CMS-64 form that states submit to the Centers for Medicare and Medicaid Services in order to receive their matching grant payments. The data contain all expenditures that qualify for federal matching and are supported by documentation such as invoices, cost records, and eligibility reports. The expenditures in these data are typically higher than those reported in the Medicaid Statistical Information System (MSIS), since MSIS only contains claims payments, whereas FMR contains supplemental payments (e.g., disproportionate share hospital payments) that are also federally reimbursable (National Research Council, 2010). The main outcome variable in this study uses the “total current expenditures” line from the FMR.

The expenditure data is also broken down by detailed categories of spending. To create the broad spending categories used in the study, I follow the service type grouping used in the various MACStats reports since 2011. Specifically, each of the broad categories contain expenditures in the FMR as follows:

- Hospital: Inpatient and outpatient hospitals; emergency hospital services; emergency services for aliens; critical access hospitals

- Long-term institutional care: Mental health facilities; nursing facilities; intermediate care facilities for persons with intellectual disabilities

- Long-term non-institutional care: Home health services; home and community-based services; personal care services; private duty nursing; rehabilitative services; hospice

- Acute care: Physician and surgical services; dental services; other practitioners; clinic services; laboratory and radiological services; sterilization; abortions; early and periodic screening, diagnostic, treatment screening; rural health; targeted case management; federally qualified health centers; non-emergency medical transport; physical therapy; occupational therapy; speech and hearing services; prosthetic devices, dentures, and eyeglasses; diagnostic screening and preventative services; nurse
midwife; nurse practitioner; school based services; freestanding birth center; health homes; tobacco cessation; other care services

- Drugs: Prescribed drugs; drug rebates

- Medicare: Medicare premiums for Part A and B; payments for Qualified Medicare Beneficiaries; Medicare coinsurance payments

- Managed care: Managed care organizations; prepaid ambulatory health plans; prepaid inpatient health plans; group health payments; primary care case management; all inclusive care for the elderly

A.2 Beneficiary Data

This study uses data on the number of beneficiaries from the Medicaid Statistical Information System (MSIS) state summary tables. Although state reporting to MSIS was voluntary before 1999, MSIS data is generally available through 2011 for most state-years (and incompletely for 2012). However, a transition to a new reporting system, the Transformed MSIS (T-MSIS), interrupted the availability of Medicaid enrollment data in later years.²⁰

MSIS summary tables contain state-level information on the number of “beneficiaries” as well as the number of “eligibles.” A “beneficiary” is a person on behalf of whom Medicaid has made a payment while “eligibles” are enrollees who were covered for at least one day in the fiscal year. Since data on eligibles are only available starting in 1991, I use “beneficiaries” as my primary measure of persons served by a state’s Medicaid program to examine as long a period as possible. Generally, the number of eligibles is slightly higher than the number of beneficiaries (but not always). Starting in 1998, states began including in their beneficiary counts managed care enrollees (even if the managed care enrollee does not actually use any services). This can be seen in Appendix Figure A.4, where there is a noticeable upward jump in the total number of beneficiaries. This change in accounting brings the number of beneficiaries measure closer to the number of eligibles, depending on the proportion of a state’s Medicaid caseload that is in managed care.

To extend my analysis as far forward as possible, I supplement the MSIS data with enrollment from MACStats reports, which are derived from MSIS data. The reports contain enrollment counts (rounded to the nearest thousand) for fiscal years 2011 to 2013 (2014 data is missing for many states). While in

²⁰Beginning in 2014, Medicaid enrollment was also reported in the Medicaid Budget and Expenditure System (MBES), but these data, reported quarterly, are not directly comparable to those in the MSIS system.
theory these enrollment numbers should correspond to the number of “eligibles” in MSIS summary tables, a comparison of the numbers in 2011 and 2012 (the years of overlap) indicates that the enrollment and eligibles counts do not always match and that the number of enrollees are sometimes closer to the number of beneficiaries. Appendix Figure A.4 shows that the total number of enrollees in MACStats appears to more closely follow the number of beneficiaries in the MSIS summary tables. Given this, I use MACStats enrollment counts in 2011-2013 to extend the beneficiary series forward.\textsuperscript{21}

To sum up, much of the data on beneficiaries used in this study count the numbers of managed care enrollees and individuals who have used a Medicaid-paid service in a fee-for-service setting, and these numbers are therefore somewhere in between the actual number enrolled and the number who utilize Medicaid services. Data in the last few years correspond to the number of enrollees, but may be calculated using a different methodology. To account for potential effects of changing data sources and methodology over time, I show that my results are robust to including year fixed effects.

\section*{B Alternative Identification Strategy and Results}

This section presents estimates of the stimulative effect of the Medicaid match rate using an alternative identification strategy. Specifically, it leverages changes in match rates within states that are due to sharp changes in the inputs to the match rate formulas (e.g., population updates or revisions to personal income calculations).

Recall that the formula determining the match rate for state \( s \) in year \( t \) is

\[
FMAP_{s,t} = \max \left\{ 0.5, 1 - 0.45 \left( \frac{PCPI_{s,t}}{PCPI_{US,t}} \right)^2 \right\}
\]

where \( PCPI_{s,t} \) and \( PCPI_{US,t} \) are the average per-capita personal incomes of state \( s \) and nationally, respectively, of the most recent three years prior to \( t \) for which data is available. State personal income is calculated by the Bureau of Economic Analysis and is occasionally updated to incorporate new or revised data sources or methodology. Comprehensive revisions, which result in the largest changes, take place about every five years to harmonize with National Income and Product Accounts. On top of personal income changes,

\textsuperscript{21}It is worth mentioning that although the Medicaid Analytic Extract (MAX) Chartbooks of 2012 and 2013 also have information on the number of beneficiaries, they do not appear to match the MSIS summary tables either (even though the MAX data are derived from the same MSIS system). This may be because MAX statistics are reported by calendar year rather than fiscal year.
per-capita personal income calculations may also shift when population estimates are updated. Population estimates are typically substantively updated only after administration of the Decennial Census.

Yearly changes in the per-capita personal income are therefore driven by two factors: 1) an actual change in a state’s “true” per-capita personal income and 2) changes in per-capita personal income due to revised methodology (e.g., as a result of a comprehensive revision). To isolate (a portion of) the yearly change that is due purely to exogenous updates in estimation methodology, note that the $PCPI_{s,t}$ ($PCPI_{US,t}$) is the average of the state’s (national) per-capita income for the last three years that data is available. Therefore, if we define $m_{s,t} \equiv \frac{PCPI_{s,t}}{PCPI_{US,t}}$, then

$$m_{s,t} = \frac{\text{pcpi}_{s,t-3}^4 + \text{pcpi}_{s,t-4}^4 + \text{pcpi}_{s,t-5}^4}{\text{pcpi}_{US,t-3}^2 + \text{pcpi}_{US,t-4}^2 + \text{pcpi}_{US,t-5}^2}$$

where $\text{pcpi}_{s,t}^r$ is the period $t$ per-capita personal income of region $j \in \{s,US\}$, as published at time $r$, where $r > t$.22 Consider the following predicted relative per-capita personal income,

$$\tilde{m}_{s,t} = \frac{\text{pcpi}_{s,t-3}^r + \text{pcpi}_{s,t-4}^r + \text{pcpi}_{s,t-5}^r}{\text{pcpi}_{US,t-3}^r + \text{pcpi}_{US,t-4}^r + \text{pcpi}_{US,t-5}^r}$$

The difference between $\tilde{m}_{s,t}$ and $m_{s,t}$ is that the second and third terms of both the numerator and denominator in $\tilde{m}_{s,t}$ use the previous year’s vintage of per-capita personal income estimates. Note that since these terms are inputs for calculating $m_{s,t-1}$, they also partially determine the previous year’s match rate. Thus, we can decompose the yearly change in the state’s relative per-capita personal income $m_{s,t} - m_{s,t-1}$ into two additive parts: 1) $\tilde{m}_{s,t} - m_{s,t-1}$ can be thought of as the yearly change due to incorporating the most recent year of per-capita income, and 2) $m_{s,t} - \tilde{m}_{s,t}$ is the component of the change due to methodology revisions.23 Indeed, when we examine the 100 largest jumps in $m_{s,t} - \tilde{m}_{s,t}$ over the 1985-2013 sample period, 65 of them occurred in the nine years where data was updated due to the Decennial Census or a comprehensive revision.

I examine Medicaid spending in the years before and after large changes (“shocks”) in the exogenous component $m_{s,t} - \tilde{m}_{s,t}$ within a state, where large is defined as $|m_{s,t} - \tilde{m}_{s,t}| > 0.005$. This roughly corresponds to the upper and lower 15th percentiles of the shock distribution and balances using only large shocks that might plausibly be attributed to methodological updates and sample size considerations. I first show, using

---

22The match rate for fiscal year $t$ is determined in year $t-1$, at which point only year $t-2$ reports are available.

23While it is true that the first terms of the numerator and denominator of $\tilde{m}_{s,t}$, $\text{pcpi}_{s,t-3}^r$ and $\text{pcpi}_{US,t-3}^r$, may reflect both a true change in the per-capita income and revised methodology, we do not observe $\text{pcpi}_{s,t-3}^r$ (i.e., the most recent per-capita income calculated using the previous year’s methodology) and therefore cannot fully decompose these terms.
an event study specification, that large changes in $m_{s,t} - \tilde{m}_{s,t}$ indeed lead to sharp changes in the match rate for several years. I then show the change in Medicaid spending before and after these large shocks in $m_{s,t} - \tilde{m}_{s,t}$.

The event study specification is as follows:

$$y_{it} = \sum_{k \neq -1} \delta^k D^k_{it} + \gamma_t + \alpha_i + \epsilon_{it}$$

where $y_{it}$ is the outcome (e.g., spending) associated with PCPI shock $i$ and year $t$. The set of variables $D^k_{it}$ are indicators that equal one if it is $k$th year after the shock $i$ in year $t$ (zero otherwise). $\gamma_t$ and $\alpha_i$ are year- and “shock-” level fixed effects, respectively. I estimate this model using data that are balanced five years around each PCPI shock, which effectively focuses on revisions in the 1990-2008 period. Standard errors are clustered at the state level.

Appendix Figure A.5 shows effects of PCPI shocks on the FMAP by plotting the estimated coefficients $\delta^k$ in a model where the outcome is the match rate, separately for positive and negative shocks. We see that a positive PCPI revision (i.e., one where the PCPI is lower than expected) has a clear first stage effect on the match rate, increasing it by about 1.2 percentage points over several years, while a negative revision has the opposite effect of reducing the match rate by about 0.9 percentage points. The next set of graphs shown in Appendix Figure A.6 indicate that although the PCPI revisions had an effect on the match rates, there were no visually appreciable effects on the Medicaid spending per beneficiary.

To summarize the magnitude of these effects, let $ShockMagnitude_i$ equal to the size of the shock associated with PCPI revision $i$ (i.e., $m_{s,t} - \tilde{m}_{s,t}$). I estimate

$$y_{it} = \beta FMAP_{it} + \gamma_t + \alpha_i + \epsilon_{it}$$

where $FMAP_{it}$ is the match rate in year $t$, and instrument $FMAP_{it}$ with the $ShockMagnitude_i \times Post_t$, where $Post_t$ is equal to 1 if $t$ is a post-revision year for revision $i$, and 0 otherwise. This equation will be estimated on the same data covering the five years pre- and post-shock. As before, standard errors are clustered at the state level. The estimates, shown in Appendix Table A.5, separately estimate effects for positive and negative shocks, to correspond to Appendix Figure A.6, and also combine all shocks together. All the estimates confirm that the effect of the match rate on per-beneficiary Medicaid expenditures is statistically
indistinguishable from zero. However, the estimates are quite imprecise, as a 95 percent confidence interval can only rule out per-beneficiary spending effects larger than $283 per percentage point increase in the match rate (column 3).

C Welfare Effects of Medicaid Financing Reform: Model Details

C.1 Planner Problem

To obtain the optimal match rate, the federal government maximizes social welfare subject to a balanced budget constraint. That is, it solves:

$$\max_{\{\theta_i\}} \sum_{i=1}^{S} g_i [U_i(B_i, \bar{B}) + W_i - (1 - \theta_i)P_iB_i - \tau_i]$$

such that

$$\sum_{i=1}^{S} \theta_i P_i B_i = \sum_{i=1}^{S} \tau_i$$

The first order condition with respect to $\theta_i$ is

$$g_i [U_i(1 - \theta_i)P_i] \frac{dB_i}{d\theta_i} + g_i P_i B_i - \sum_{j=1}^{S} g_j \frac{d\tau_j}{d\theta_i} + \sum_{j=1}^{S} g_j U_j \bar{B} \frac{dB_j}{d\theta_i} = 0$$

The first term is equal to zero due to the state’s maximizing behavior. The second term is a mechanical effect of raising state $i$’s match rate on its income. The third term is the effect of raising the lump-sum tax (on all states) in order to fund the matching grant change. The fourth term reflects the spillover impact of increasing state $i$’s Medicaid spending.

Note the budget balance condition implies

$$\sum_{j=1}^{S} \frac{d\tau_j}{d\theta_i} = P_i B_i (1 + \epsilon_i)$$

where $\epsilon_i = \frac{dB_i}{d\theta_i} \theta_i$. The expression indicates that any change in spending must be paid for through increases in lump-sum taxes, but does not specify how each state’s taxes will be affected. Suppose then that each state $j$ is responsible for $\omega_j$ share of the increased outlays. Then $\frac{d\tau_j}{d\theta_i} = \omega_j P_i B_i (1 + \epsilon_i)$ where $\sum_{j=1}^{S} \omega_j = 1$. (In the
main text, \( \omega_j = \frac{1}{S} \) for all \( j \) for simplicity.)

The first order condition then simplifies to

\[
g_i P_i B_i - (1 + \varepsilon_i) P_i B_i \sum_{j=1}^{S} g_j \omega_j + \frac{\varepsilon_i B_i}{\theta_i} \sum_{j=1}^{S} g_j U_j \frac{dB}{dB_i} = 0
\]

Rearranging,

\[
\theta_i = \frac{\sum_{j=1}^{S} g_j U_j \frac{dB}{dB_i}}{P_i \bar{g} \overline{\omega}} \cdot \frac{\varepsilon_i}{1 + \varepsilon_i - \frac{g_i}{\bar{g} \overline{\omega}}}
\]

where \( \bar{g} \overline{\omega} \equiv \sum_{i=1}^{S} g_i \omega_i \). Again using the fact that \( \bar{B} = \frac{\sum P_i B_i}{\sum P_i} \),

\[
\theta_i = \frac{\sum_{j=1}^{S} g_j U_j \frac{dB}{dB_i}}{\bar{g} \sum_{j=1}^{S} P_j} \cdot \frac{\varepsilon_i}{1 + \varepsilon_i - \frac{g_i}{\bar{g}}}
\]

As noted above, the main text uses the simplification that \( \omega_j = \frac{1}{S} \) for all states \( j \), so that the match rate expression is simply

\[
\theta_i = \frac{\sum_{j=1}^{S} g_j U_j \frac{dB}{dB_i}}{\bar{g} \sum_{j=1}^{S} P_j} \cdot \frac{\varepsilon_i}{1 + \varepsilon_i - \frac{g_i}{\bar{g}}}
\]

where \( \bar{g} = \frac{1}{S} \sum_{i=1}^{S} g_i \). While the exact expression does depend on the values of \( \omega_j \), I ultimately use the optimal match rate expression to infer the quantities \( \frac{\sum_{j=1}^{S} g_j U_j \frac{dB}{dB_i}}{\bar{g} \overline{\omega}} \) and \( \frac{g_i}{\bar{g} \overline{\omega}} \), which are sufficient to conduct a comparative welfare analysis with the appropriate normalization, as shown below.

### C.2 Welfare Effects of a Reform

Suppose that the match rates changes from \( \theta^* \) to \( \theta \). If spending in state \( i \) under match rate \( \theta_i^* \) is given by \( B_i^* \), total Medicaid spending is \( B^* \), and the lump-sum tax required to fund the system is \( \tau^* \), total social welfare under matching regime \( \theta^* \) is

\[
\sum_{i=1}^{S} g_i [U_i(B_i^*, \bar{B}^*) + W_i - (1 - \theta_i^*) P_i B_i^* - \tau_i^*]
\]

while total social welfare under the reformed regime \( \theta \) is

\[
\sum_{i=1}^{S} g_i [U_i(B_i, \bar{B}) + W_i - (1 - \theta_i) P_i B_i - \tau_i]
\]
The difference is
\[
\sum_{i=1}^{S} g_i [U_i(B_i, \bar{B}) - U_i(B_i^*, \bar{B}^*) - (1 - \theta_i)P_i(B_i - B_i^*) - (\theta_i^* - \theta_i)P_iB_i^* - (\tau_i - \tau_i^*)]
\]

Using the approximations that
\[
U_i(B_i, \bar{B}) - U_i(B_i^*, \bar{B}) \approx U_{i1} \cdot (B_i - B_i^*)
\]

\[
U_i(B_i^*, \bar{B}) - U_i(B_i^*, \bar{B}^*) \approx U_{i2} \cdot (\bar{B} - \bar{B}^*)
\]

and noting that state i’s first order condition is \(U_{i1} = (1 - \theta_i)P_i\), the welfare difference can be approximated by
\[
\sum_{i=1}^{S} g_i [(\theta_i - \theta_i^*)P_iB_i^* - (\tau_i - \tau_i^*)] + (\bar{B} - \bar{B}^*) \sum_{i=1}^{S} g_i U_{i2}
\]

Finally, normalizing by \(\frac{g_i}{\bar{g}}\) gives
\[
\sum_{i=1}^{S} g_i \left[(\theta_i - \theta_i^*)P_iB_i^* - (\tau_i - \tau_i^*)\right] + (\bar{B} - \bar{B}^*) \sum_{i=1}^{S} g_i U_{i2} \frac{\bar{g}}{\bar{g}}
\]

**C.3 Allowing for Income Effects**

Consider the more general state utility function \(U_i(B_i, \bar{B}, X_i)\). As before, states choose Medicaid spending \(B_i\) and non-Medicaid spending \(X_i\) to maximize state utility subject to budget constraint \(X_i + (1 - \theta_i)P_iB_i = W_i - \tau_i\), where \(\theta_i\) is the Medicaid match rate, \(P_i\) is the number of Medicaid beneficiaries in the state, \(W_i\) is an exogenous state budget, and \(\tau_i\) is a lump-sum tax to the federal government used to fund the Medicaid grants. The difference between this case and the one presented in Section 6 is that the utility of the state is no longer quasi-linear and there may be income effects on Medicaid spending.

In this case, the optimal match rate is the solution to the maximization problem:
\[
\max_{\{\theta_i\}_{i=1}^{S}} \sum_{i=1}^{S} g_i [U_i(B_i, \bar{B}, W_i - (1 - \theta_i)P_iB_i - \tau_i)]
\]
such that

\[ \sum_{i=1}^{S} \theta_i P_i B_i = \sum_{i=1}^{S} \tau_i \]

which yields

\[ \theta_i = \frac{\sum_{j=1}^{S} g_j U_{j2}}{g U_3 \sum P_j} \cdot \frac{e_i}{(1 + e_i) - \frac{g_i U_{i3}}{g U_3}} \]

where

\[ g U_3 = \frac{1}{S} \sum_{i=1}^{S} g_i U_{i3} \]

The welfare change associated with a financing reform will be given by

\[ \sum_{i=1}^{S} g_i [U_i(B_i, \bar{B}, W_i - (1 - \theta_i) P_i B_i - \tau_i) - U_i(B^*_i, \bar{B}^*, W_i - (1 - \theta^*_i) P_i B^*_i - \tau^*_i)] \]

where, as in the main text, the * denotes the Medicaid spending and financing parameters of the current (old) regime. This welfare change can be approximated by the following expression

\[ \sum_{i=1}^{S} g_i U_{i3} \cdot [((\theta_i - \theta^*_i) P_i B^*_i - (\tau_i - \tau^*_i)) + (\bar{B} - \bar{B}^*) \sum_{i=1}^{S} g_i U_{i2}] \]

and after normalizing by \( g U_3 = \frac{1}{S} \sum_{j=1}^{S} g_j U_{j3} \),

\[ \sum_{i=1}^{S} \frac{g_i U_{i3}}{g U_3} \cdot [((\theta_i - \theta^*_i) P_i B^*_i - (\tau_i - \tau^*_i)) + (\bar{B} - \bar{B}^*) \sum_{i=1}^{S} \frac{g_i U_{i2}}{g U_3}] \]

This expression means that, with the proper normalization to convert the welfare expression into a money metric, one can use the same method as discussed in Section 6 to infer welfare weights and externality valuations from the current matching grant system. That is, by assuming the current matching system is optimal, expression (6) provides the required values of \( \sum_{j=1}^{S} g_j U_{j2} / g U_3 \) and \( g U_{i3} / g U_3 \).

While the inclusion of income effects minimally changes the welfare expression and the calculation of the social welfare weights, it does also affect how one measures the change in national Medicaid spending in simulating a block grant reform. Specifically, without income effects, the reduction in national Medicaid spending for a block grant reform simply requires a price elasticity. However, with income effects, one also

\[ \text{To obtain } \frac{\sum_{i=1}^{S} g_i U_{i2}}{g U_3}, \text{ one must assume that the social weights for states at the match rate floor of 50 percent are such that } g_i U_{i3} \text{ are equalized.} \]
needs to take into account any effects from the size of the grant. Since few studies have credibly calculated the income effects of Medicaid spending, I use as a proxy the income elasticity of 0.29 estimated by Baicker (2005) for AFDC benefits. I assume that a 10 percent increase in the size of the federal grant increases national per beneficiary Medicaid spending by 2.9 percent. Using this estimate, I revisit the same questions as in the main text: For a reform that simply converts the current matching grants into block grants (i.e., that respects the current allocation of grants), how much larger would block grants need to be to maintain welfare? I find that with the assumed income effects, block grants need to be 38 percent larger (instead of 41 percent without accounting for income effects). For a reform that reallocates grants according to population size and state income, as proposed by Clemens and Ippolito (2018), I find that block grants need to be 36 percent larger (instead of 39 percent without accounting for income effects).
Figure A.1: Number of Observations in Each Bin of Relative PCPI

Notes: Sample includes all states 1985-2013 except AK for all years and AZ 1985-1990. Each point represents the count of observations falling within the bin of relative state PCPI. Bins are of width 0.025. The kink point, where state PCPI = $\sqrt{\frac{0.5}{0.45}} \cdot$ (national PCPI) is normalized to be at 0, is denoted by the vertical line.
Notes: Sample includes all states 1985-2013 except AK for all years and AZ 1985-1990. Each point represents the average predicted Medicaid spending per beneficiary for the observations within the bin of relative state PCPI, where prediction is done by regressing spending on the state’s average age, percent of the population under age 18, over 64, with at least a high school education, female, and in poverty, the unemployment rate, and the population size. Bins are of width 0.025. The kink point, where $\text{state PCPI} = \sqrt{\frac{0.5}{0.45}} \cdot \text{(national PCPI)}$ is normalized to be at 0, is denoted by the vertical line.
Notes: Each point is an estimate of the effect of the match rate on per-beneficiary Medicaid spending from separate RKD regressions using observations within the bandwidth indicated. The shaded areas indicate 95 percent confidence intervals, where standard errors are clustered at the state level. The dashed vertical lines denote optimal bandwidths calculated following Calonico et al. (2014). Panel B presents the same information as Panel A, with the axes adjusted for ease of visualization.
Figure A.4: Total Beneficiaries and Eligibles Across Data Sources

Notes: This graph plots the total number of “beneficiaries” (MSIS), “eligibles” (MSIS), and enrollees (MACStats) in the U.S. Each point includes all states except: (MSIS beneficiaries) AZ before 1991, ME in 2011; (MSIS eligibles) RI before 1995, NH in 1994; ME in 2011.
Figure A.5: Effect of PCPI Shocks on Federal Match Rates

Panel A: Positive Shock

Panel B: Negative Shock

Notes: Each graph plots the estimated event-study coefficients around large revisions ("shocks") in per-capita personal income. A “positive” ("negative") shock is one in which the PCPI is smaller (larger) than expected. The outcome in each regression is the percentage of Medicaid expenditures funded by the federal government (i.e., federal match). The shaded areas indicate 95 percent confidence intervals, where standard errors are clustered at the state level.
Figure A.6: Effect of PCPI Shocks on Medicaid Spending Per Beneficiary

Panel A: Positive Shock

Panel B: Negative Shock

Notes: Each graph plots the estimated event-study coefficients around large revisions ("shocks") in per-capita personal income. A “positive” ("negative") shock is one in which the PCPI is smaller (larger) than expected. The outcome in each regression is Medicaid spending per beneficiary. The shaded areas indicate 95 percent confidence intervals, where standard errors are clustered at the state level.
Table A.1: Asymptotic Mean-Squared Error Estimates for RKD Results

<table>
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<tr>
<th>Bandwidth</th>
<th>Poly Order</th>
<th>Total (1)</th>
<th>Federal Share (2)</th>
<th>State Share (3)</th>
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<td>p=1</td>
<td>100344</td>
<td>35603</td>
<td>16413</td>
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<td>16305</td>
<td>2481</td>
<td>6410</td>
</tr>
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<td>p=1</td>
<td>6432</td>
<td>3282</td>
<td>584</td>
</tr>
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<td>665799</td>
<td>168206</td>
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<td>41824</td>
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<td>2414717</td>
<td>650980</td>
<td>558288</td>
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<td>1131419</td>
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</tr>
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<td>2417146</td>
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</table>

Notes: Each estimate of asymptotic mean squared error is obtained following Pei et al. (2020), using the package `rdmse`. "opt" denotes the optimal bandwidth calculated per Calonico et al. (2014).
Table A.2: RKD Estimates of Match Rate on Medicaid Spending and Beneficiaries (with Year Fixed Effects and Covariates)

<table>
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<tr>
<th>Bandwidth</th>
<th>Poly Order</th>
<th>First Stage Bandwidth</th>
<th>Expenditures Per Beneficiary</th>
<th>Expenditures Per Poor</th>
<th>Beneficiaries Per Poor</th>
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</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>(1)</td>
<td>Total Federal Share State Share</td>
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<td></td>
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<td>[0.0100]</td>
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Notes: Each cell in the column “First Stage” is an estimate of change in the slope in the federal match rate moving from the right to the left of the threshold, using different bandwidths and polynomial orders. Each cell for the subsequent columns represents an estimate of the effect of a percentage point increase in the federal match rate on the outcome denoted in the column heading for various specifications. "Poly Order" denotes the polynomial order. "Per Poor" measures express spending and beneficiaries divided by the number of people in poverty. Each specification includes year fixed effects and controls for state’s average age, percent of the population under age 18, over 64, with at least a high school education, female, and in poverty, the unemployment rate, and the population size. Standard errors (in brackets) are clustered at the state level.
Table A.3: Estimates of State-Level Characteristic Kinks

<table>
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<tr>
<th>Bandwidth Poly Order</th>
<th>Avg. Age</th>
<th>% Children</th>
<th>% Elderly</th>
<th>% HS and Above</th>
<th>% Female</th>
<th>% In Poverty</th>
<th>Unemp. Rate</th>
<th>Population Size (000s)</th>
<th>Covariate Index</th>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>p=1</td>
<td>-7.56</td>
<td>2.42</td>
<td>-22.42</td>
<td>36.30</td>
<td>-14.87</td>
<td>-1.35</td>
<td>16.00</td>
<td>-56127.12</td>
<td>-4748.26</td>
</tr>
<tr>
<td></td>
<td>[9.24]</td>
<td>[9.34]</td>
<td>[11.18]</td>
<td>[27.53]</td>
<td>[5.52]</td>
<td>[15.40]</td>
<td>[10.85]</td>
<td>[43860.23]</td>
<td>[4127.28]</td>
</tr>
<tr>
<td>p=2</td>
<td>-50.94</td>
<td>40.37</td>
<td>-89.46</td>
<td>18.98</td>
<td>-19.86</td>
<td>-1.92</td>
<td>-9.86</td>
<td>53291.60</td>
<td>-13222.52</td>
</tr>
<tr>
<td></td>
<td>[41.23]</td>
<td>[42.04]</td>
<td>[41.07]</td>
<td>[92.41]</td>
<td>[14.92]</td>
<td>[57.84]</td>
<td>[40.19]</td>
<td>[155034.93]</td>
<td>[14676.95]</td>
</tr>
</tbody>
</table>

Notes: Each cell is an estimate of change in slope in the state characteristic denoted by the column heading moving from the right to the left of the threshold, using different bandwidths and polynomial orders. The covariate index in last column is constructed by first regressing Medicaid expenditures per beneficiary on all the characteristics in the previous columns, and then using the prediction from that regression. Standard errors (in brackets) are clustered at the state level.
Table A.4: RKD Estimates of Match Rate Impacts on Adjusted Medicaid Spending
Expenditures Per Beneficiary

<table>
<thead>
<tr>
<th></th>
<th>Total (net of est. IGT/taxes)</th>
<th>Federal Share (net of est. IGT/taxes)</th>
<th>State Share (net of est. IGT/taxes)</th>
</tr>
</thead>
<tbody>
<tr>
<td>RK Estimate</td>
<td>237.54</td>
<td>169.28</td>
<td>68.26</td>
</tr>
<tr>
<td></td>
<td>[47.88]</td>
<td>[34.72]</td>
<td>[19.70]</td>
</tr>
<tr>
<td>Value at Thrs</td>
<td>6408.74</td>
<td>3525.37</td>
<td>2883.36</td>
</tr>
</tbody>
</table>

Notes: The estimates in the first row show the impact of a percentage point increase in the federal match on the outcome denoted by the column heading, using a local linear specification with a bandwidth of 0.3. The second row shows the estimated outcome at the threshold. “Total (net of est. IGT/taxes)” and “State (net of est. IGT/taxes)” are estimated Medicaid spending per beneficiary after accounting for intergovernmental transfers from providers to states and provider taxes. See text for details. Standard errors (in brackets) are clustered at the state level.
Table A.5: Estimated Effects of PCPI Revisions on Medicaid Spending

<table>
<thead>
<tr>
<th></th>
<th>Positive Shock</th>
<th></th>
<th>Negative Shock</th>
<th></th>
<th>All</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>FS</td>
<td>IV</td>
<td>FS</td>
<td>IV</td>
<td>FS</td>
</tr>
<tr>
<td></td>
<td>$ Per Beneficiary</td>
<td>(1)</td>
<td>$ Per Beneficiary</td>
<td>(2)</td>
<td>$ Per Beneficiary</td>
</tr>
<tr>
<td>Shock x Post</td>
<td>-64.57</td>
<td>[19.95]</td>
<td>-68.88</td>
<td>[36.01]</td>
<td>-52.92</td>
</tr>
<tr>
<td>FMAP</td>
<td>-197.09</td>
<td>[182.31]</td>
<td>172.69</td>
<td>[320.98]</td>
<td>-75.63</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td>N</td>
<td>1454</td>
<td>1454</td>
<td>1517</td>
<td>1517</td>
<td>2739</td>
</tr>
<tr>
<td>Number of Shocks</td>
<td>119</td>
<td>119</td>
<td>130</td>
<td>130</td>
<td>249</td>
</tr>
</tbody>
</table>

Notes: Each column represents a different regression. "FMAP" is the federal match percentage, calculated as the percentage of Medicaid expenditures that is funded by the federal government. "FS" are first stage estimates of the effect of PCPI revisions on the match rate and "IV" are instrumental variables estimates of the match rate on Medicaid spending per beneficiary. A “positive” (“negative”) shock is one in which the PCPI is smaller (larger) than expected. Standard errors (in brackets) are clustered at the state level.