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Abstract

Almost all recent literature on Medicaid and labor supply has used Affordable Care Act (ACA)-induced Medicaid eligibility expansions in various states as natural experiments. Estimated effects on employment and earnings differ widely due to differences in the scope of eligibility expansion across states. Using a Regression Kink Design (RKD) framework, this paper takes a uniquely different approach to the identification of the effect of Medicaid generosity on household income. Both state-level data and March CPS data from 1980–2013 suggest that generous federal funding of state-level Medicaid costs have a modest negative effect on household income. The negative impact of Medicaid generosity on household income is more pronounced at the lower end of the household income distribution and on the income and earnings of female heads.

Keywords: Medicaid, Household Income, Labor Supply

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1. Introduction

Medicaid is by far the largest means-tested transfer program in the U.S. and has experienced explosive long-term growth in both program expenditure and enrollment (Figure 1). The program has assumed added significance following recent Affordable Care Act (ACA)-aided expansions. Economists have long argued that a means-tested anti-poverty program such as Medicaid, while improving health outcomes and helping alleviate poverty, can have important behavioral effects that can undermine program effectiveness and offset associated economic gains. Because Medicaid eligibility is tied to low household income and limited asset ownership, the program generates natural incentives to curb household earnings and savings.

In estimating Medicaid's effect on labor supply and earnings, the recent literature has mostly used ACA-induced Medicaid eligibility expansions in various states as natural experiments. Estimated effects on employment and earnings differ widely due to differences in the scope of eligibility expansions across states. A potential concern regarding state-by-state eligibility experiments is that they may be endogenous to state policy (Gruber, 2000). Moreover, state-specific experiences may not be broadly applicable at the national level (Buchmullar et al., 2015).

Drawing upon nationally representative data, this paper uses a plausibly more exogenous measure of Medicaid generosity to estimate the program's effect on labor market outcomes. Leung (2016) recently showed that the Federal Medical Assistance Percentage (FMAP)—the formula-based federal matching rate for states' Medicaid costs—is highly correlated with states' Medicaid expenditure per enrollee, a key indicator of Medicaid generosity. Building on the evidence in Leung (2016), this paper takes a uniquely different approach to identifying the effect of Medicaid generosity on household income and makes two contributions. First, utilizing the FMAP as a proxy for Medicaid's generosity, I use the kink in the relationship between FMAP and the assignment variable—state per-capita income relative to the nation —to estimate the effect of Medicaid's generosity on household income and earnings in a Regression Kink Design (RKD) framework (Card et. al., 2012; 2015). Second, using data from the March CPS from 1980–2013, I estimate Medicaid's impact across different quantiles of household income and earnings.

To be more precise, the FMAP is a kinked function of the assignment variable—the ratio of the 3-year average of the lagged state per-capita personal income to that of the lagged U.S. per-capita personal income. For example, the FMAP for 2013 is based on 3-year averages of state and national per-capita personal incomes from 2008, 2009, and 2010. Thus there is no mechanical reason for a kink in the relationship between current household income and an assignment variable based on a ratio that is multiple years lagged by the time the FMAP becomes effective.

This paper is the first to uncover definitive evidence of a kink in the relationship between household income and state per-capita income relative to the nation. It closely aligns with the kink in FMAP as a function of state per-capita income relative to the nation, suggesting a potential link between Medicaid generosity and household income. While the kink location is known, tests for an unknown kink in the relationship between household income and the assignment variable reveals strongest evidence of a kink precisely at the known kink location, with significantly weaker evidence of a kink at other "placebo" kink locations.

Analysis using March supplements of IPUMS-CPS data reveals that increases in FMAP—a proxy for Medicaid generosity—significantly lowers household income at the bottom quantiles of the household income distribution—the part of the income distribution that has the highest incidence of Medicaid eligibility. A one percentage point increase in FMAP is associated with a 3-6 percent decline in household income at the 20th percentile of the household income distribution and 4-11 percent reduction in total income of prime-age single female heads. The RKD estimated effects are small and insignificant for groups typically not affected by Medicaid—for example, upper quantiles of the household income and earnings distribution, and married couples without children. While the magnitudes of RKD estimates at the lower quantiles of household income distribution are sensitive to inclusion of state and year fixed effects and state effects by linear trends, their signs remain remarkably robust.

By estimating Medicaid's effect on household income, the paper addresses an important gap in the previous literature, which has mostly focused on individual labor supply response, as the impact on household income is key to understanding the program's role in alleviating poverty (Ben-Shalom, Moffitt, and Scholz, 2011). The paper's findings have important policy implications. First, a modest negative effect of Medicaid on household income suggests that ignoring the effect would upwardly bias the program's estimated impact on poverty reduction. Secondly, contrary to an overwhelming prior evidence of generally small and insignificant income effects on labor supply and earnings, this paper's findings imply a non-trivial income effect on household income from the Medicaid-induced outward shift in the household budget constraint (Figure 2).

In addition to a predominantly negative income effect apparent from Figure 2, two other factors suggest that Medicaid should lower household income. First, Medicaid eligibility may be asset-tested, with significant incentives to reduce saving and wealth accumulation (Hubbard et al, 1999).[1] Secondly, even in the absence of asset-tests, public assistance programs such as Medicaid tend to discourage precautionary saving. Both would lead to a lower household income through reduced unearned income.

But other factors lead to ambiguous theoretical predictions on the Medicaid-household income relationship that must be resolved empirically. For example, the existence of eligibility thresholds, based on household income, creates opposing labor supply incentives for households just below and above the threshold. Households just above the cutoff would reduce their household income to qualify for Medicaid coverage, those below the threshold should increase the labor supply.

Additionally, public health insurance coverage such as Medicaid should generally lead to better health outcomes, which may improve labor market prospects, earnings, and household income. Furthermore, Medicaid expansions could crowd out private health insurance and potentially generate both a substitution effect—through higher wages on a new job that doesn't provide health insurance—and an income effect—through reduced medical expenditure (Dave et al., 2015; Cutler and Gruber, 1996). The boost to household income from both of these channels could be partially offset by reduced labor supply among individuals who worked largely to maintain employer-provided health insurance. Finally, as noted in Kaestner et al. (2015), Medicaid could potentially increase household labor supply due to a stimulative effect on the economy.

The paper's unique approach to identification of Medicaid's overall effect on household income comes with some caveats. An important concern is that estimates using household income, rather than individual labor supply responses used in previous research, are subject to biases due to changes in family composition. However, this concern is partially mitigated by controlling for number of children and family size and by restricting the sample to female heads. Finally, FMAP is at best an imperfect proxy for Medicaid generosity and, therefore, estimates may simply represent an aggregate macroeconomic effect of changes in FMAP rather than changes in the Medicaid eligibility.

[1] The number of states using assets to determine eligibility for Medicaid has declined sharply over the years.

The rest of the paper proceeds as follows. Section 2 summarizes the recent literature on the labor market effects of Medicaid. Section 3 describes the data and Section 4, the econometric framework and identification. Section 5 reports the results and discusses key findings. Finally, there is a brief conclusion.

2. The Previous Literature

As documented in comprehensive reviews of Buchmueller et al (2015) and Bitler and Zavodney (2014), earlier work faced the challenge of disentangling the labor market effects of Medicaid from that of the cash assistance program Aid to Families with Dependent Children (AFDC), as there were significant linkages between the two—eligibility for AFDC was a prerequisite for qualification for Medicaid for nondisabled adults. This created a welfare lock, with individuals staying on AFDC simply to qualify for Medicaid. The two programs started to delink following the Deficit Reduction Act of 1986. The decoupling further intensified after the welfare reforms following the Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA) in the 1990's with many states implementing significant Medicaid expansions.

Using the cross-state variation in Medicaid generosity over time, Yelowitz (1995) found significant effect on employment of female-headed households. Subsequent studies, however, detected small and insignificant effect of Medicaid (Ham and Shore-Sheppard, 2005; Meyer and Rosenbaum, 2001). Montgomery and Navin (2000) examined the labor supply behavior of female heads using the March CPS and found that results were sensitive to fixed and random effects specifications.

Recent studies exploited changes in Medicaid eligibility across a handful of individual states—Tennessee, Wisconsin, and Oregon—and found mixed evidence on the estimated impact on employment and earnings. While Garthweight et al (2014) found that loss of Medicaid led to a 63 percent increase in employment in Tennessee, Dague et al (2014) found that Medicaid reduced employment by 5.5 percentage points (12 percent) and lowered quarterly earnings by $300 among Medicaid enrollees in Wisconsin. Dave, et al. (2015) found that the increase in 20 percentage points in Medicaid eligibility among pregnant women and the associated crowd out of private coverage led to 11–13 percent decline in employment among pregnant women and 13–16 percent decline among unmarried pregnant women without a high school degree.

Most other studies found rather insignificant effects of Medicaid on employment and labor supply. Using exogenous variation from the Oregon lottery experiment, Baicker et. al. (2014) found no significant effect of Medicaid coverage on employment or earnings. Leung and Mas (2016) compared childless adults in states expanding Medicaid with those that didn't before and after the ACA and found positive effect on coverage but insignificant effects on employment. Kaestner et al (2015) also studied the impact of ACA Medicaid expansions on health insurance coverage and labor supply of low-educated and low-income adults and found that while Medicaid coverage increased by 50 percent, it had a positive but insignificant effect on work effort. CBO (2014) also predicted a rather small negative effect of ACA-Medicaid expansions on labor supply.[2] Gooptu et. al (2016) found that following the ACA, there were no significant effects of more generous Medicaid eligibility on labor force transitions of employment to unemployment or from full-time to part-time employment for low-income adults. Hamersma and Kim (2009) found that Medicaid did reduce "job lock" but the impact of most other outcomes were insignificant. More recently, Duggan, Goda, Jackson (2017) also found empirically ambiguous effects of the ACA on labor supply, with increases in labor force participation in areas with higher potential Medicaid enrollment offsetting declines in areas with higher ACA exchange enrollment.

3. Data and Summary Statistics

Analysis in this paper is primarily based on the March supplements of IPUMS-CPS data (Flood et al. 2017).[3] More specifically, IPUMS-CPS is the source of data on the key outcome variables—household income and earnings—and other demographic covariates. Household income is the sum of pre-tax money incomes of all members in the household. It includes income from wages, business, farm, interest, dividends, rents, retirement, and public assistance and social insurance programs. All income measures refer to the previous calendar year, i.e., the year prior to the survey year. I covert all nominal income variables to real 2016 dollars using the CPI.

FMAP and per-capita personal income

[2] See The Budget and Economic Outlook: 2014 to 2024 (February 2014), Appendix C, www.cbo.gov/publication/45010
[3] The data is downloaded from https://cps.ipums.org/cps/.

FMAP data are from the U.S. Department of Health and Human Services (HHS) and data on per-personal income for the US and states are from the Bureau of Economic Analysis (BEA). FMAP for state s and year t is a formula that governs the federal share of total Medicaid cost incurred by a state to provide health services covered under the program and is given by:

$$FMAP_{st} = min\left(max\left(0.5,\ 1 - 0.45 * \left(\frac{\overline{PCPI_{st}}}{PCPI_t^{US}} \right)^2 \right),\ 0.83 \right) \qquad (1)$$

$\overline{PCPI_{st}}$ and $PCPI_t^{US}$ are 3-year average PCPIs for state s in year t and U.S. in year t, respectively. For year t they are calculated based on PCPI in years $t-3$, $t-3$, and $t-4$.

$$\overline{PCPI_{st}} = (PCPI_{st-3} + PCPI_{st-4} + PCPI_{st-5})/3$$

$$\overline{PCPI_t^{US}} = (PCPI_{t-3}^{US} + PCPI_{t-4}^{US} + PCPI_{t-5}^{US})/3$$

The FMAP is 55 percent if the State's per capita personal income (SPCPI) equals the national average (USPCPI). It varies inversely with the state's per capita income relative to the nation, i.e., $\frac{\overline{PCPI_{st}}}{PCPI_t^{US}}$. The FMAP has a floor of 50 percent, which induces a kink in the relationship between FMAP and $\frac{\overline{PCPI_{st}}}{PCPI_t^{US}}$ when $\frac{\overline{PCPI_{st}}}{PCPI_t^{US}}$ equals 1.054, so that FMAP is greater than 0.5 if $\frac{\overline{PCPI_{st}}}{PCPI_t^{US}}$ is under 1.054 and FMAP equals 0.5 if $\frac{\overline{PCPI_{st}}}{PCPI_t^{US}}$ exceeds 1.054. The ceiling of 83 percent on the FMAP almost never binds.

The FMAP has remained largely unchanged since its inception and states have no control over it. Therefore it is not subject to the policy or legislative endogeneity that is a potential concern in research using individual state-by-state experiences. As detailed in Mitchell (2016), there have been some instances when the FMAP has deviated from the formula. For example, the FMAP for DC is set at 70 percent regardless of its relative per capita income. Also, as part of the ACA, the FMAP increased to allow 100 percent reimbursement to states for newly eligible Medicaid enrollees in states that opted for Medicaid expansion under the ACA. The FMAP was also increased in 2003-2004 to assist states during a slow economic recovery. After the Great Recession, in 2007–09, it was allowed to deviate from the formula and was linked to the state's unemployment rate. There were also temporary adjustments for Alaska, Michigan, and Louisiana (due to Hurricane Katrina).

In addition to Medicaid funding, FMAP is also used for some other relatively smaller programs: Guardianship Assistance, Child Care and Development Block Grant, Child Care mandatory and matching funds of the Child Care and Development Fund, Foster Care- Title IV-E, Adoption Assistance, and the phased down state contribution or the *clawback* for Medicare—Part D. Additionally, the Children's Health Insurance Program (CHIP) uses enhanced FMAP (E-FMAP) which equals $FMAP + 0.3 \times (1 - FMAP)$ with a cap of 85 percent. Thus E-FMAP also has a kink with respect to RPCI at the same place as FMAP. So the estimates in the paper should be interpreted as pertaining to both, the Medicaid and the CHIP programs.

Analysis Sample

The analysis sample consists of data from 1980-1981, 1985–2002, 2005–08, 2012, and 2013.[4] Remaining years are dropped because the traditional FMAP-relative per-capita income relationship underwent significant changes during periods of economic downturn and due to the ACA. For the same reason, data from DC, AK, MN (1986-1987), VT (2006-2008) are also excluded from analysis. These sample restrictions are similar to Leung (2016). The paper has two sets of results for the impact of Medicaid FMAP as a proxy for Medicaid generosity—(1) the impact on household income and earnings quantiles and (2) the effect on single female head of households. Results on household income and earnings quantiles are based on data on household heads aged 19 years or older. The female heads sample is restricted to prime age unmarried female heads of households between 22-60 years of age, where the household head is the only member in the household with positive income. Appendix Table A1 presents the summary statistics for key variables.

4. Econometric Framework and Identification

The econometric specification is based on the Regression Kink Design (RKD) approach proposed in Card et al. (2012). In this framework, let the outcome variable be some measure of real income (*Y*) and suppose there is a suitable proxy for Medicaid Generosity (*M*). Also suppose M is a deterministic function of an assignment variable R with a known kink in the function $M(R)$ at $R = R_0$. Let $Y = y(M, R, U)$ have the following relationship with M and R:

$$Y = \beta M(R) + f(R) + u$$

Then the RKD estimate of the effect of M on Y is given by:

[4] These years are the reference years for the income variable—household income and earnings.

$$\beta^{RKD} = E\left[\frac{\partial Y}{\partial M}\middle| R = R_0\right] = \frac{\lim_{R\to R_0^+} \frac{\partial E[Y|R=R_0]}{\partial R} - \lim_{R\to R_0^-} \frac{\partial E[Y|R=R_0]}{\partial R}}{\lim_{R\to R_0^+} \frac{\partial M(R)}{\partial R} - \lim_{R\to R_0^-} \frac{\partial M(R)}{\partial R}}$$

As discussed in Card et. al (2012), the numerator represents the change in slope of the conditional expectation of the outcome variable Y at the kink point R_0 and the denominator contains the deterministic change in slope of the continuous treatment variable M, at the kink point $R = R_0$. In the RKD terminology M is the continuous treatment variable and R is the assignment (or running) variable. Card et. al (2012) showed that β^{RKD} identifies the treatment effect on the treated if the density of the assignment variable (R) evolves smoothly and the treatment assignment rule is continuous at the kink point. β^{RKD} is estimated from the following polynomial regression using observations around a sufficiently close neighborhood of bandwidth (h) around the kink point:

$$Y = \gamma_0 + \sum_{j=1}^{p}\left[\gamma_j(R - R_0)^j + \beta_j(R - R_0)^j \times D\right] + u \qquad (2)$$

In equation (2), D is a dummy for R being above the kink point R_0, p is the order of the polynomial. The estimated coefficient on the linear interaction term, β_1, represents the reduced form effect of the running variable R on Y. For a linear polynomial, the estimation collapses to a simple regression of Y on $(R - R_0)$ and the interaction term $(R - R_0) \times D$. The coefficient on the linear interaction term β_1 is an estimate of the difference in slope of the outcome Y with respect to R at the kink point. The sharp RKD estimate of the impact of the treatment variable M on Y is then obtained by normalizing β_1 by the deterministic (and mostly known) change in the slope of the assignment variable R at the kink point.

Using the RKD framework, Leung (2016) found that the statutory FMAP, i.e. the federal share of a state's cost of Medicaid services, has a strong positive effect on the state-level Medicaid spending per enrollee, a widely used proxy for Medicaid generosity.[5] In the remainder of the paper, I use the FMAP as a proxy for Medicaid generosity (M). $\frac{\overline{PCPI_{st}}}{\overline{PCPI_t^{US}}}$ is the assignment variable (R)– henceforth denoted RPCI. Because the kink in the FMAP-RPCI relationship is at RPCI=1.054, $R - R_0$ in equation (2) is simply RPCI -1.054. As per usual practice, throughout the estimation I

[5] For example see Winkler (1991).

normalize RPCI to zero at the kink point by using the difference (RPCI -1.054), henceforth denoted K.

Due to periodic revisions in RPCI, the assignment variable is observed with error. Therefore, I estimate a fuzzy RKD that simply involves normalizing β_1 by the size of the estimated kink in FMAP-RPCI relationship, i.e., the coefficient from an auxiliary RKD regression of FMAP on a constant, the observed K, and $K \times D$. My estimates should be interpreted as the causal effect of a change in Medicaid generosity—as encapsulated in FMAP—on household income.

In this paper I focus primarily on the effect of Medicaid generosity on quantiles of household income and earnings. Let $Q_{Y_{ist}}(\tau)$ be the τ_{th} quantile of household income measure, Y_{ist}, for state s in year t. Let K_{st} represent the normalized assignment or running variable for state s in year t, D_{st} a dummy variable for state s in year t being above the kink ($K_{st} > 0$), and X_{st} is a vector of other state-year level covariates. Also let $u_{st}(\tau)$ represent state-year level unobservables affecting $Q_{Y_{ist}}(\tau)$.

I estimate the following model in a simple linear RKD framework:

$$Q_{Y_{ist}}(\tau) = \gamma_0 + \gamma_1(\tau)K_{st} + \beta_1(\tau)K_{st} \times D_{st} + X_{st}\delta(\tau) + u_{st}(\tau) \qquad (3)$$

The key identifying assumption is that state-year level unobserved factors ($u_{st}(\tau)$) are uncorrelated with the location with respect to the kink point of the state s in year t. As shown in Chetverikov, Larsen, and Palmer (2016), due to the presence of group level (state-year) unobservables, the standard quantile regression estimator (Koenkar and Basset, 1978) would be inconsistent. They show that, in a setting with exogenous group-level covariates, there is a simple two-step grouped-quantile regression alternative to the standard quantile regression.

First, calculate the τ_{th} quantile of Y_{ist} for each state s and year t. And then a simple OLS of the τ_{th} state-year level quantiles on other right-hand-side covariates—K_{st}, $K_{st} \times D_{st}$, and X_{st}—in the second step would yield consistent estimates of all the coefficients including the RKD effect for the τ_{th} quantile, $\beta_1(\tau)$. The key identification assumptions are that u_{st} is uncorrelated with $K_{st}$and D_{st} , which will be violated if, for example, states are able to manipulate their location with respect to the kink point or if there are kinks in other state level unobservables at the same location as the kink in FMAP-RPCI relationship.

If the key RKD identification assumptions are satisfied then the RKD estimates are identified even without any covariates in the specification; covariates are useful just for improving precision. Although I examine robustness of the estimates to inclusion of covariates, my basic RKD estimates of $\beta_1(\tau)$ are based on estimating (3) without covariates, X_{st}. In additional specifications, I also estimate $\beta_1(\tau)$ by estimating specifications with a quadratic RKD polynomial. All standards errors reported in the paper are clustered at the state level.

5. Estimation Results

Figure 3 plots the theoretical relationship between the running variable RPCI and FMAP, calculated using the formula in (3). Because the BEA periodically revises the per-capita income estimates, the actual RPCI underlying the FMAP are not observed and is measured with error. Figure 4 shows that the relationship between observed RPCI and FMAP deviates from the exact formula-based relationship shown in Figure 3, due to revisions in BEA's personal income data originally used when FMAP is published. Figure 5 presents binned scatterplots of the bottom quartile of log real household income (Log RHHI) averaged over bins of RPCI (with bin width set to 0.04), and shows visual evidence of the kink in the bottom quartile of household income.

The location of the kink in the Log RHHI-RPCI relationship appears to closely align with the kink in the FMAP-RPCI relationship, suggesting a potential link between FMAP and Log RHHI. The size of the kink in Log RHHI relative to the size of the kink in FMAP essentially yields an estimate of the impact of FMAP on Log RHHI. If FMAP is a valid proxy for Medicaid generosity then this ratio can be interpreted as the RKD estimate of the impact of Medicaid generosity on household income.

5.1 Test of identification assumptions

The validity of the RKD approach relies on the assumption that states should be able to precisely manipulate their RPCI around the location of the kink in FMAP-RPCI relationship. A violation of this key assumption would imply that the kink itself is endogenous and RKD invalid. This can be informally tested by examining whether the density of RPCI evolves continuously around the kink point. Figure 6 plots the density of RPCI around the kink location and, using the Mccrary test for the difference between the two densities on either side of the kink, shows that the densities do not differ significantly at the kink point; there is no statistical evidence of manipulation around the kink location (Mccrary, 2008). This is hardly surprising, as RPCI for state s in year t is calculated using personal income data from years $t-3, t-4,$ and $t-5$, that are already multiple years old when RPCI for year t is calculated.

While the primary RKD identification remains fundamentally untestable, another informal test is based on the absence of a kinked relationship between the running variable and other covariates, analogous to the test of covariate continuity in RD designs. Evidence of a kinked relationship in variables other than household income would cast doubt on RKD validity in this setting. Table 1 shows that most variables do not have a significant kink at the optimal bandwidth except for age, female share, and the state unemployment rate. The kinks in age and female share, however, are not surprising, as Medicaid eligibility is closely related to age and female headship; the elderly and female heads are among the most likely beneficiaries of Medicaid. Nevertheless, this concern is partly addressed by controlling for age and gender and presenting RKD estimates of the effect of Medicaid generosity on income and earnings by restricting the sample to prime-age unmarried female heads of household—a demographic group with a high incidence of Medicaid eligibility.

5.2 RKD Estimates of the effect on household income quantiles

Before examining any hard RKD estimates, Figures 7 and 8 show binned scatter plots of the deciles of log real household income calculated using all households with heads 19 years or older from March supplements of IPUMS-CPS. Log real household income is plotted against the running variable—RPCI—normalized relative to the FMAP kink point of 1.054, with bin width set to 0.04. Figure 7 shows strong visual evidence of kinks in lower household income quantiles (1^{st} -4^{th} deciles), as the slope of log real household income quantiles changes abruptly when RPCI minus 1.054 (on the horizontal axis) exceeds zero. This abrupt change in slope happens in a close neighborhood of the kink in FMAP. On the other hand, the kink disappears in the binned scatterplots of the upper quantiles (6^{th} -9^{th} decile) of household income. This serves as an informal placebo test for existence of kinks at household income quantiles clearly little affected by Medicaid generosity. The strong visual evidence of kinks at lower quantiles and their disappearance at upper quantiles is tentative evidence in favor of a real impact of Medicaid generosity on household income.

Figure 9 plots fuzzy RKD estimates and their 95 percent confidence intervals for the specification previously presented in equation (3), for a linear RKD polynomial without covariates. These estimates are for the MSE-optimal bandwidth selected using procedures in Calonico, Cattaneo, and Titiunik (2014a) and they are obtained using the "rdrobust" package discussed in Calonico, Cattaneo, and Titiunik (2014b). The RKD estimate is the largest and significantly different from zero at the 10th percentile. The estimated impact generally declines with household income until the 60th percentiles and rises somewhat, but remains well below the estimates for the 10th, 20th, and 30th percentiles. Numbers presented in Panel A of Table 2 suggest that a percentage point increase in FMAP is associated with a 3.5 percent decline in household income at the 10th-30th percentiles, a magnitude that declines to 1.8 percent at the 80th percentile before rising to 2.6 percent at the 90th percentile. The MSE-optimal bandwidth happens to be small and there appears to be a negative effect of Medicaid generosity across the entire household income distribution.

Figure 10 and Panel B of Table 2 report RKD estimates with state-level covariates: average age, share female, share white, share black, share hispanic, share of high school graduates, share with some college, share with college degree or higher. The estimates are qualitatively similar to those without covariates, but somewhat more imprecise. While estimates for the lower quantiles—10th-30th percentiles—remain similar to those from specifications without covariates, effects at the upper quantiles are substantially lower that those without covariates.

Table 3 is isomorphic to Table 2, except for the use of a quadratic RKD polynomial. All estimates remain negative, but larger than those from the linear specification. Estimates for lower percentiles are now no more significant at the 5 percent level, but are significant at a 10 percent level. For the covariate-adjusted specifications in Panel B of Table 3, a percentage point increase in FMAP is associated with a 5-6 percent decline in household income at the 10th-30th percentiles, an effect that declines to 3.6 percent at the 80th percentile and to almost zero at the 90th percentile.

Figure 11 demonstrates the sensitivity of linear RKD estimates without covariates to bandwidth choice and shows that RKD estimates are the largest for the MSE-optimal bandwidth (marked by the red dashed line). Estimates generally decline by more than 50 percent, going from a bandwidth of 0.1 to the largest bandwidth of 0.4. The significance of RKD estimates at the 80th percentile is particularly sensitive to bandwidths. The sensitivity to bandwidths for specifications with covariates were qualitatively similar and, therefore, are not reported.

Figure 12 shows R-squares from tests of unknown kinks across the distribution of possible kink points. Similar in spirit to testing for unknown multiple structural breaks in time series regressions proposed in Bai and Perron (2003), Landais (2015) extended this test in the RKD context.[6] The strongest evidence of the kink emerges when RPCI equals 1.054, with the R-square reaching its peak in a close neighborhood of the point where normalized RPCI equals zero.

Robustness

Robustness of RKD estimates is explored in Appendix Table A2, which for the local linear specification, examines robustness to an expanded set of covariates, including state and year fixed effects, and state by linear time trends. The results in columns (1) and (2) are not exactly the same as those in Table 2 because, unlike Table 2, fuzzy RKD estimates are obtained using simple two-stage least squares (2SLS) and not the "rdrobust" procedure in Calonico et. al. (2014b). RKD estimates in columns (3), (4), (5) in Panel A, that include year and state fixed effects, are qualitatively similar to those in Panel B for the full sample. All estimates remain negative, but they lose power when the specification includes state and time fixed effects as well as state effects by linear time trends in column 5. Table A2 suggests that while the sign of the RKD estimates at the lower quantiles of household income distribution are robust to inclusion of a broad set of covariates, their magnitudes are highly sensitive.

5.3 RKD Estimates for Prime-Age Single Female Heads

Given that eligibility for Medicaid is closely tied to household income, some demographic groups are likely to be more eligible than others. An important group with high eligibility for Medicaid is that of prime-age single female heads. Using binned scatterplots, Panel A of Figure 13 shows clear visual evidence of a kink in the log real household income-RPCI relationship for female heads. That evidence completely disappears in Panel B of Figure 13 when the same relationship is plotted for a group that is significantly less eligible for Medicaid—married women without children.

To further explore the impact of Medicaid generosity on female heads, I estimate a specification similar to equation (3), but for average total and wage income rather than their quantiles. It takes the following form:

$$Y_{ist} = \gamma_0 + \gamma_1 K_{st} + \beta_1 K_{st} \times D_{st} + X_{st}\delta + u_{ist} \qquad (4)$$

[6] Also see Gelber, Moore and Strand (2016) for using a similar test as a placebo test for RKD.

Restricting the sample to prime-age single female heads helps address two concerns. First, the kinks seen previously in two key covariates—female share and age—warrant an examination of RKD estimates when these two variable are held constant. And secondly, household income measures used previously do not account for any potential differences household sizes for state-year observations around the FMAP kink. I restrict the sample to prime age unmarried female heads of households between 22-60 years of age, where the household head is the only member in the household with a positive income.

Figure 14 plots RKD estimates (with their 95 percent confidence intervals) for a range of bandwidths using the linear RKD specification without covariates. Panel A shows that the RKD estimates for log total income are large and significant for the optimal bandwidth. Although the estimates decline sharply at larger bandwidths, they remain precisely estimated and negative. Almost all of the negative impact on household income operates through wage income, as seen in Panel B of Figure 14. Given that a large portion of all income for this group would consist of wages, this is not surprising. Indeed, a significant effect on nonwage income for this group would cast doubt on the RKD validity. Numbers reported in Table 4 shows that not to be the case, as the impact for nonwage income is insignificant. For the specification without covariates, Panel A of Table 4 suggests that a percentage point increase in FMAP is associated with a 8.7 percent decline in total income of female heads, and a 4.5 percent decline in wage income. With covariate adjustment in Panel B, estimates decline to 4.3 percent and 2.8 percent for total and wage income, respectively. The effects are substantially larger for the quadratic RKD specification in Table 5, but somewhat more imprecise. On the whole, Tables 4 and 5 show that Medicaid generosity negatively affects total income of female heads and that effect operates mainly through wage income. Placebo tests shown in Figure 15 further support the evidence of a significant kink in income-RPCI relationship in a close neighborhood of the actual kink in FMAP-RPCI relationship.

6. Conclusion

Building on recent work in Leung (2016), this paper takes a uniquely different approach to the identification of the effect of Medicaid generosity on household income and uncovers definitive evidence of a kink in the relationship between household income and state per-capita income relative to the nation (RPCI). The location of that kink closely aligns with a known kink in the FMAP-RPCI relationship. If FMAP is a valid proxy for Medicaid generosity, the close alignment of the two kinks suggests a potential link between Medicaid generosity and household income. The RKD estimates of the impact of FMAP on household income is more pronounced at the lower end of the household income distribution and on household income of female heads.

Using the fuzzy RKD approach, I find that increases in FMAP—a proxy for Medicaid generosity—significantly lowers household income at the bottom quantiles of the household income distribution—the part of the income distribution that has the highest incidence of Medicaid eligibility. A one percentage point increase in FMAP is associated with a 3-6 percent decline in household income at the 20th percentile of the household income distribution and 4-11 percent reduction in total income of prime-age single female heads. The RKD estimates are small and insignificant for groups typically not affected by Medicaid—for example, upper quantiles of the household income and earnings distribution, and married couples without children.

Extensive robustness tests indicate that while the sign of the RKD estimates at lower quantiles of household income distribution are robust to the inclusion of a broad set of covariates, including state and year fixed effects, their magnitudes are highly sensitive. All in all, RKD evidence points to a negative effect of Medicaid generosity, as proxied by FMAP, on the lower quantiles of household income.

The paper's findings have important policy implications. First, a negative effect of Medicaid on reported household income suggests that ignoring the effect would upwardly bias the program's estimated impact on poverty reduction. Secondly, contrary to an overwhelming prior evidence of generally small and insignificant income effects on labor supply and earnings, this paper's findings imply a non-trivial income effect of Medicaid on reported household income and earnings.

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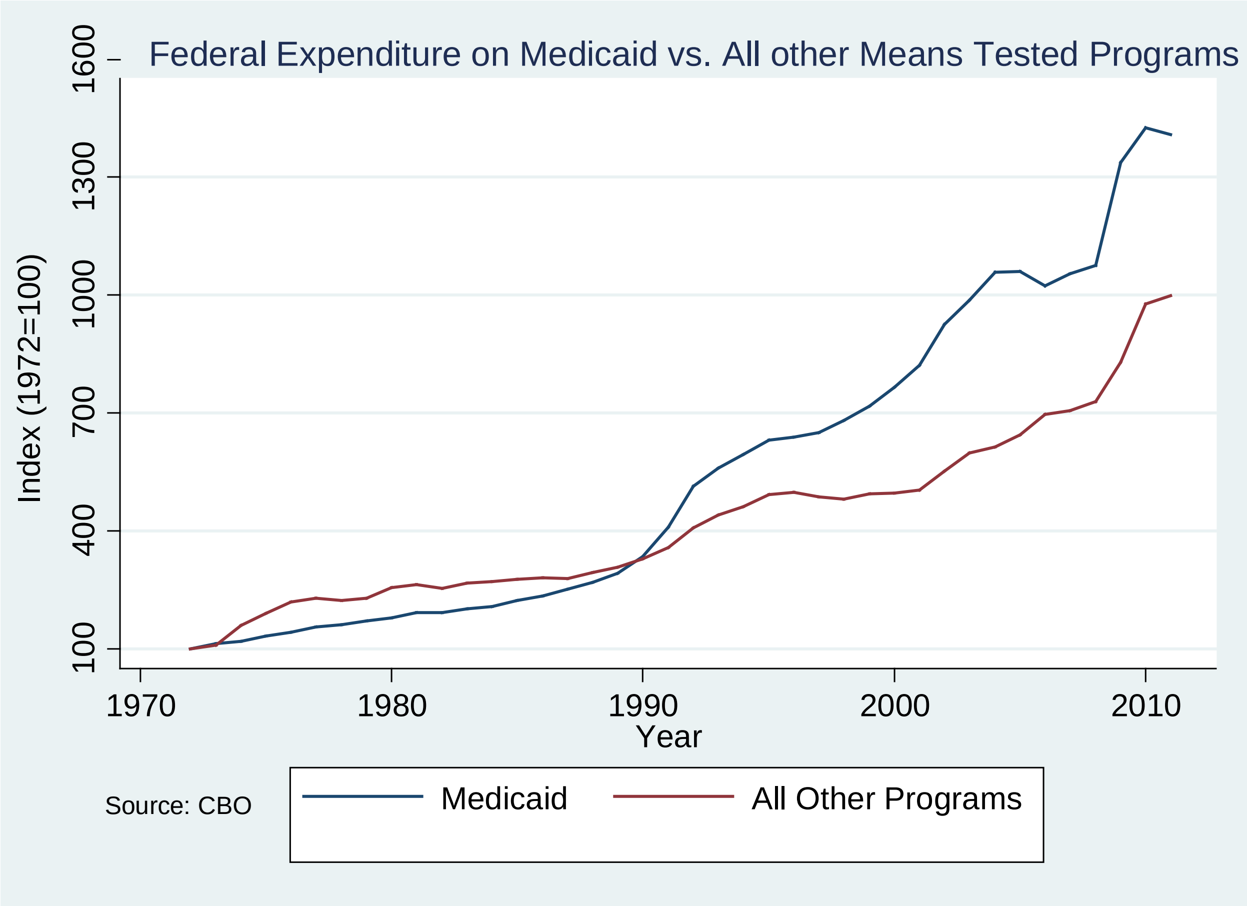
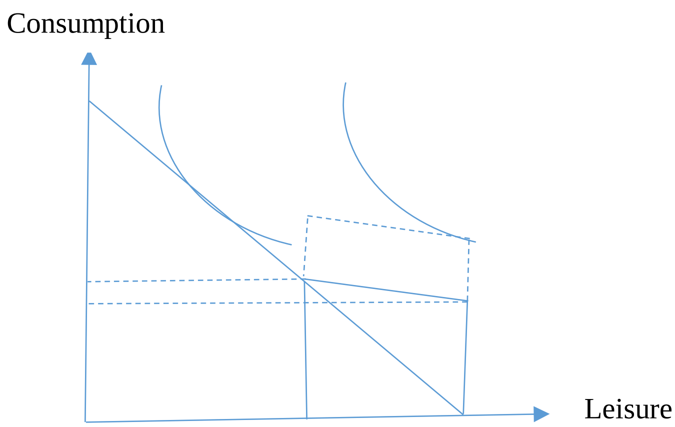
Figure 1



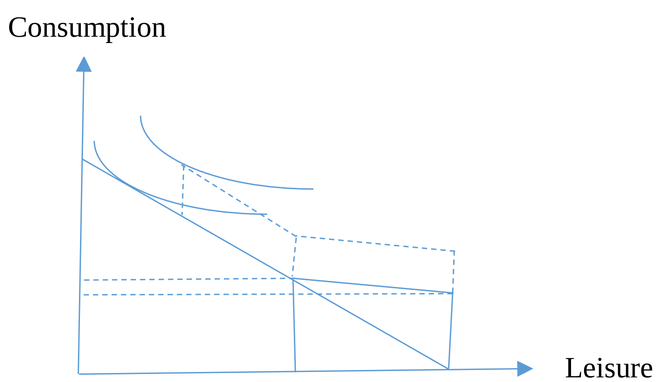
Source: CBO

Figure 2

Panel A: Decline in Labor Supply with Medicaid Tied to Cash Welfare



Panel B: Decline in Labor Supply After Medicaid Expansion



Panel C: Increase in Labor Supply After Medicaid Expansion

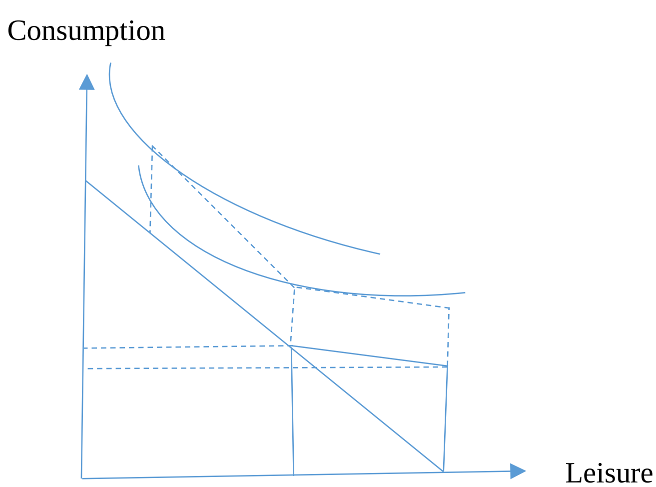
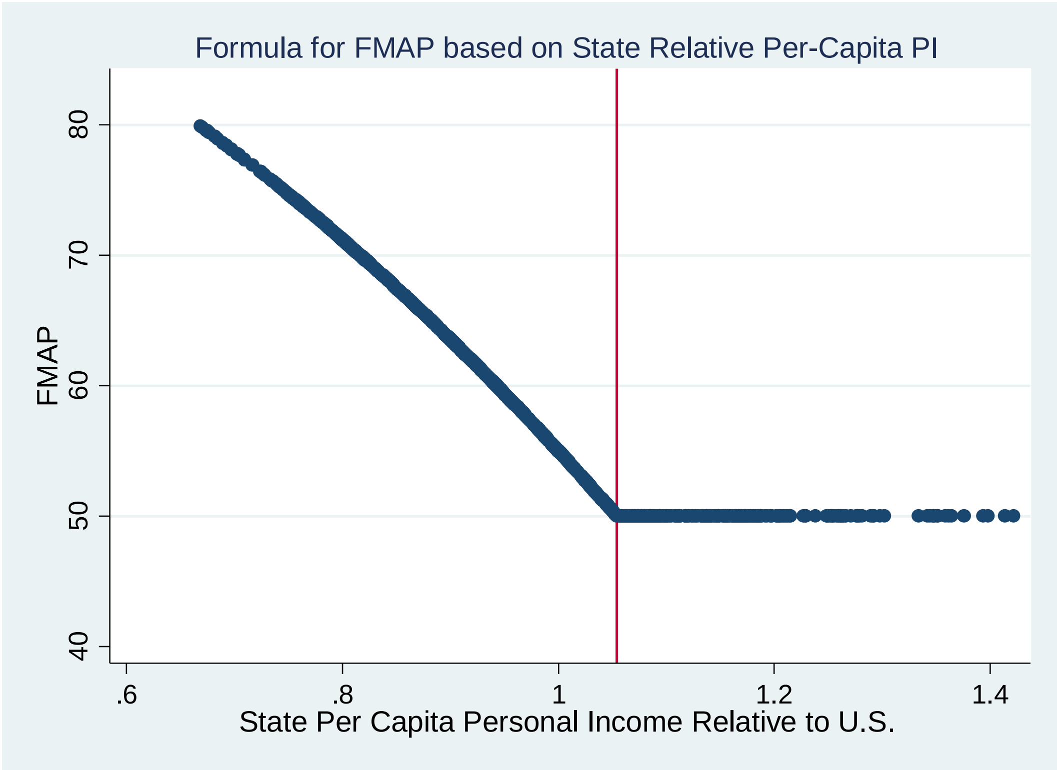
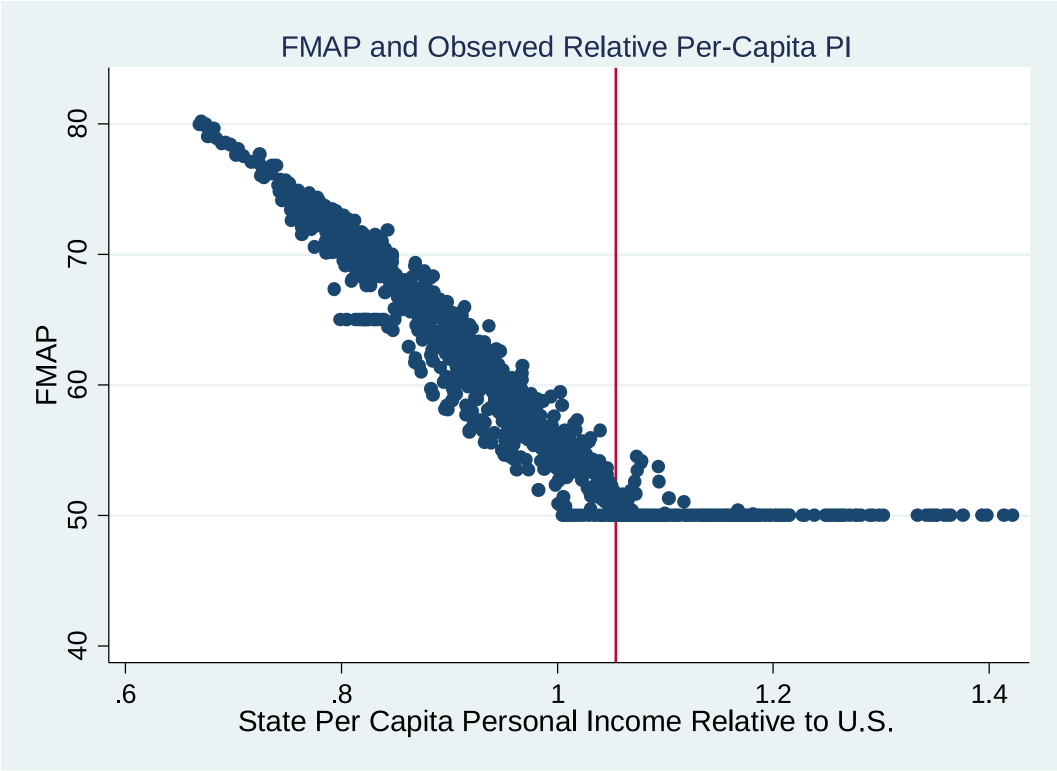


Figure 3



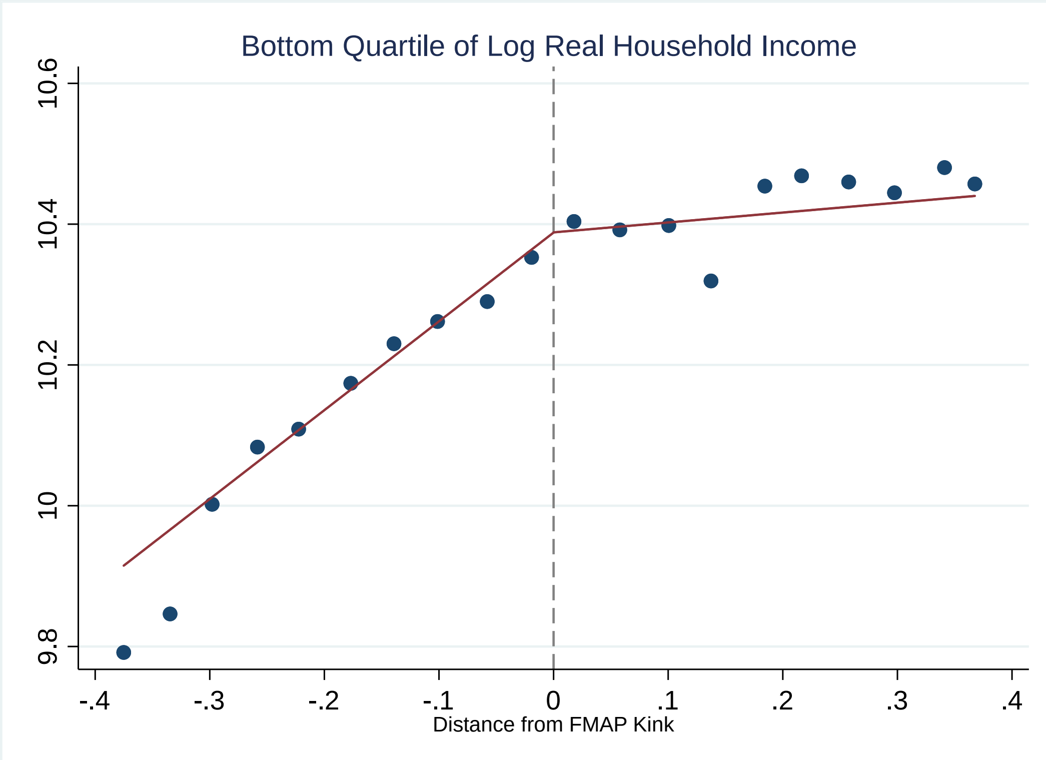
The figure plots the exact formula-based relationship between Federal Medical Assistance Percentage (FMAP) and the running variable—state's per-capita personal income relative to the nation (RPCI). FMAP equals $1 - 0.45 * RPCI^2$ and is a declining function of RPCI for RPCI values less than 1.054. FMAP reaches a floor of 50 percent when RPCI exceeds 1.054, inducing a kink in FMAP-RPCI relationship.

Figure 4



Note: The figure is based on data from 1980 to 2013 on state-year level per-capita personal income from the BEA. Data on Federal Medical Assistance Percentage (FMAP) are from U.S. Department of Health and Human Services (HHS). See text for other data sources. The figure shows binned scatter plots of FMAP against the running variable—state's per-capita personal income relative to the nation (RPCI). FMAP equals $1 - 0.45 * RPCI^2$ and is a declining function of RPCI for RPCI values less than 1.054. FMAP reaches a floor of 50 percent when RPCI exceeds 1.054, inducing a kink in FMAP-RPCI relationship. The estimated relationship between FMAP and RPCI shown in the figure deviates from the exact formula-based relationship shown in Figure 1 due to periodic revisions in BEA's personal income data originally used when FMAP is published.

Figure 5



Note: The figure shows binned scatter plots of the bottom quartile of the outcome variable (log real household income) calculate using households with heads 19 years or older from March supplements of IPUMS-CPS. Log real household income is plotted against the running variable—RPCI—normalized relative to the kink point of 1.054, with bin width set to 0.04. The figure shows that the slope of bottom quartile of Log real household income changes abruptly when RPCI *minus* 1.054 (on the horizontal axis) exceeds zero.

Figure 6

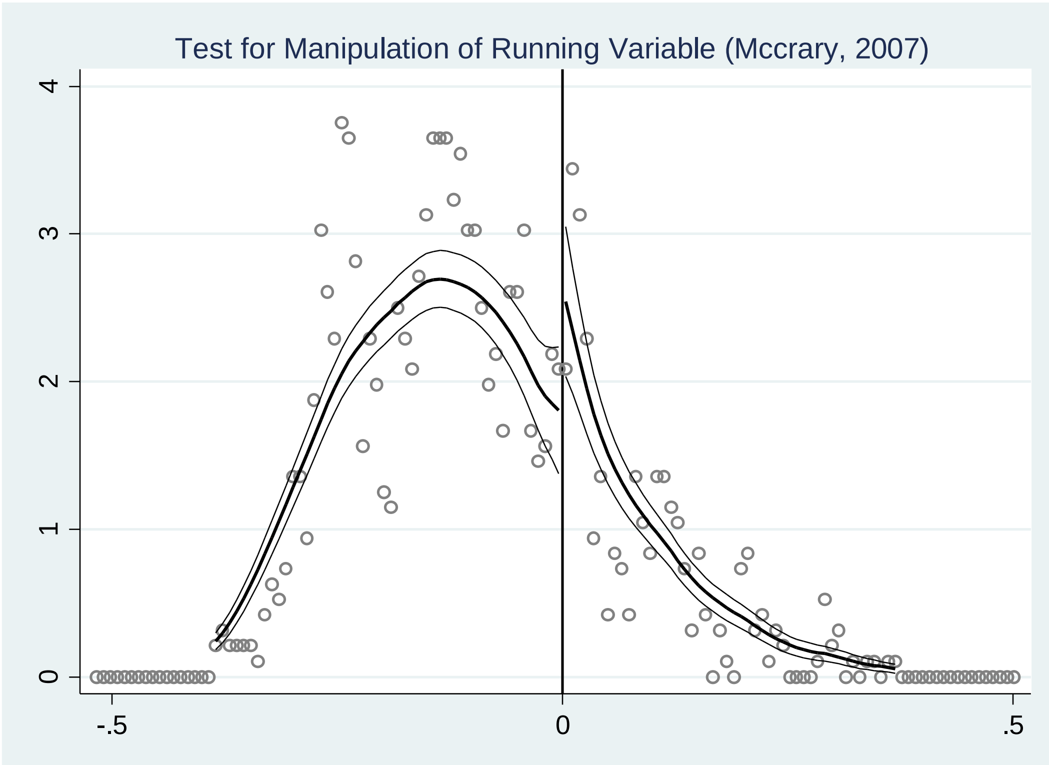
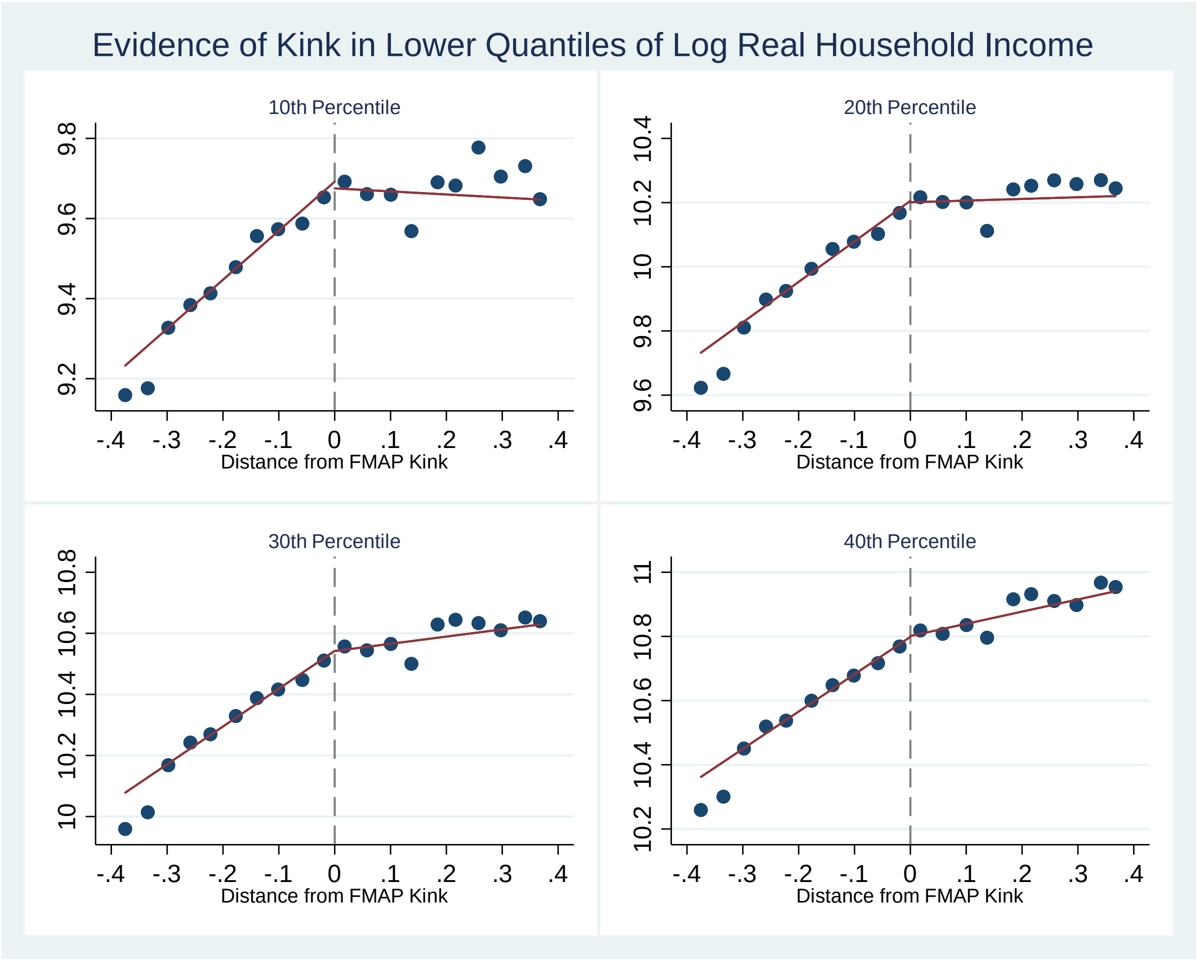
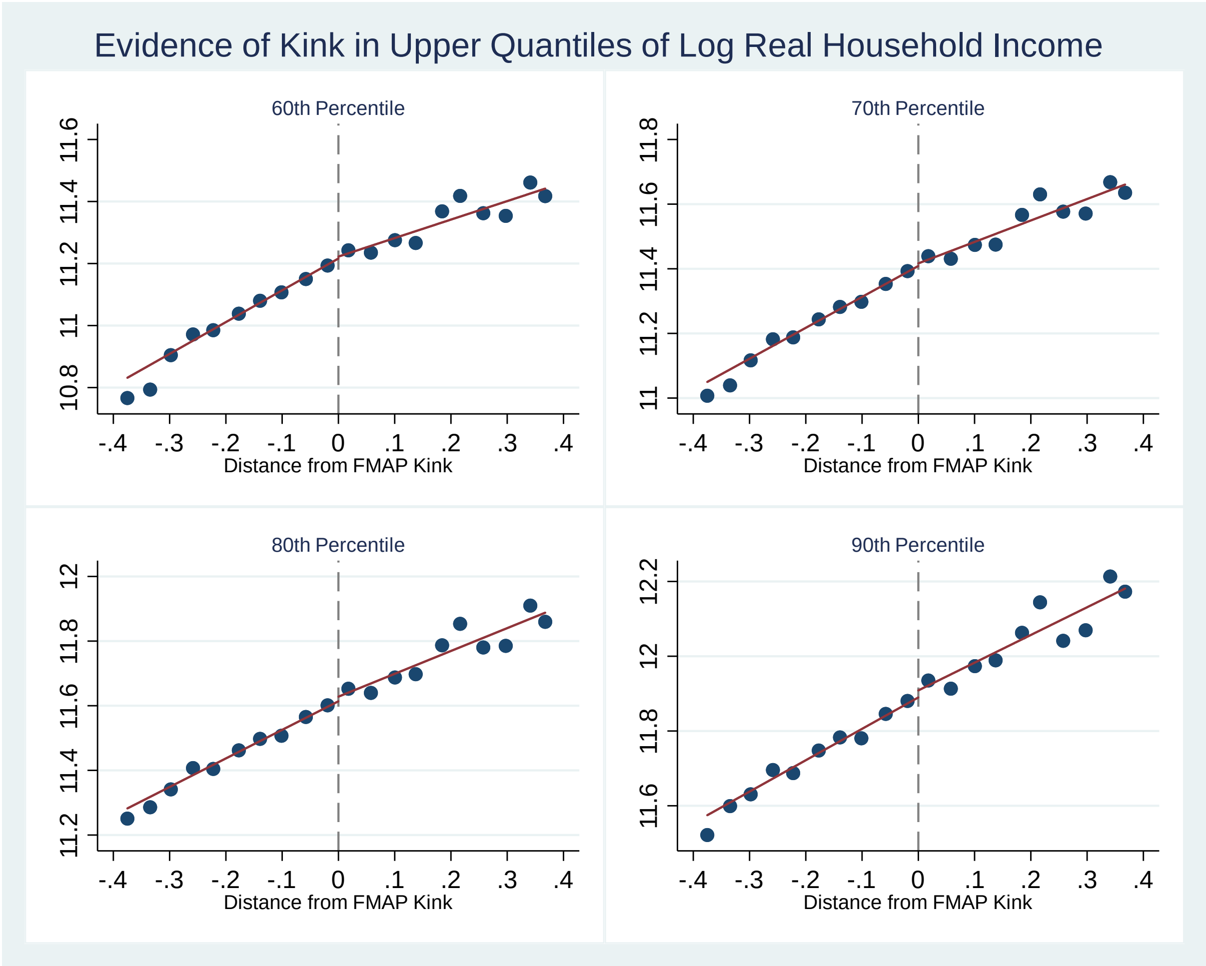

Test for Manipulation of Running Variable (Mccrary, 2007)
0
1
2
3
4
-.5
0
.5

Figure 7



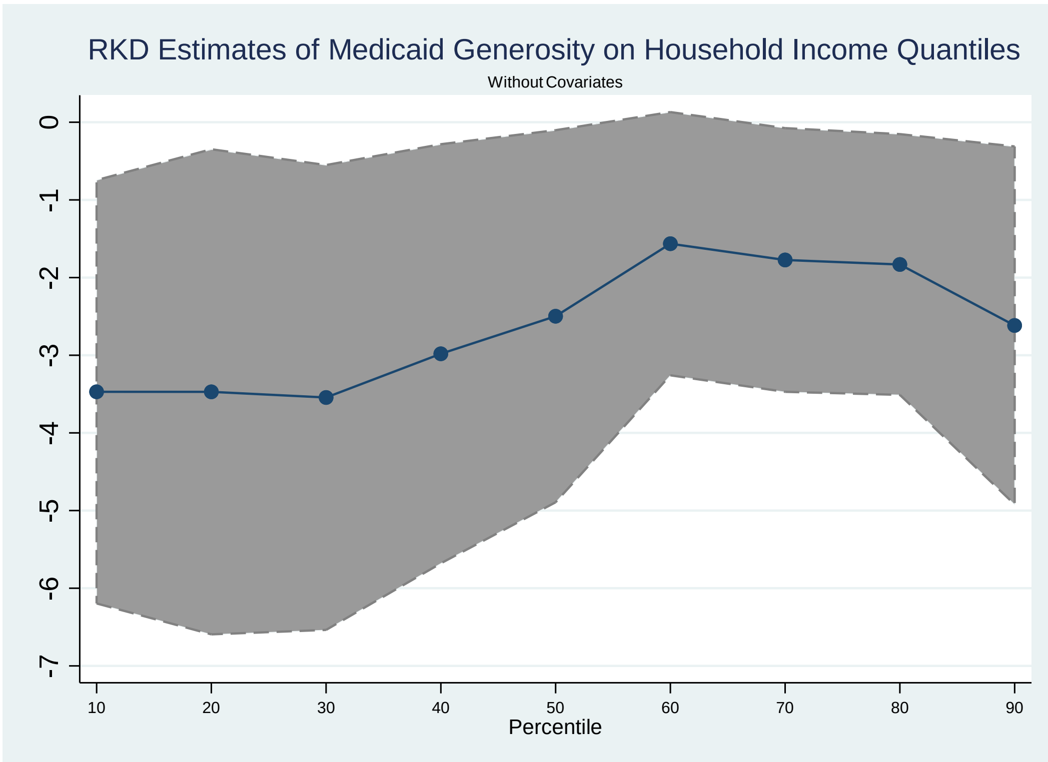
Note: The figure shows binned scatter plots of the lower quantiles of the outcome variable (log real household income) calculate using households with heads 19 years or older from March supplements of IPUMS-CPS. Log real household income is plotted against the running variable—RPCI—normalized relative to the kink point of 1.054, with bin width set to 0.04. The figure shows that the slope of lower percentiles of log real household income changes abruptly when RPCI *minus* 1.054 (on the horizontal axis) exceeds zero.

Figure 8



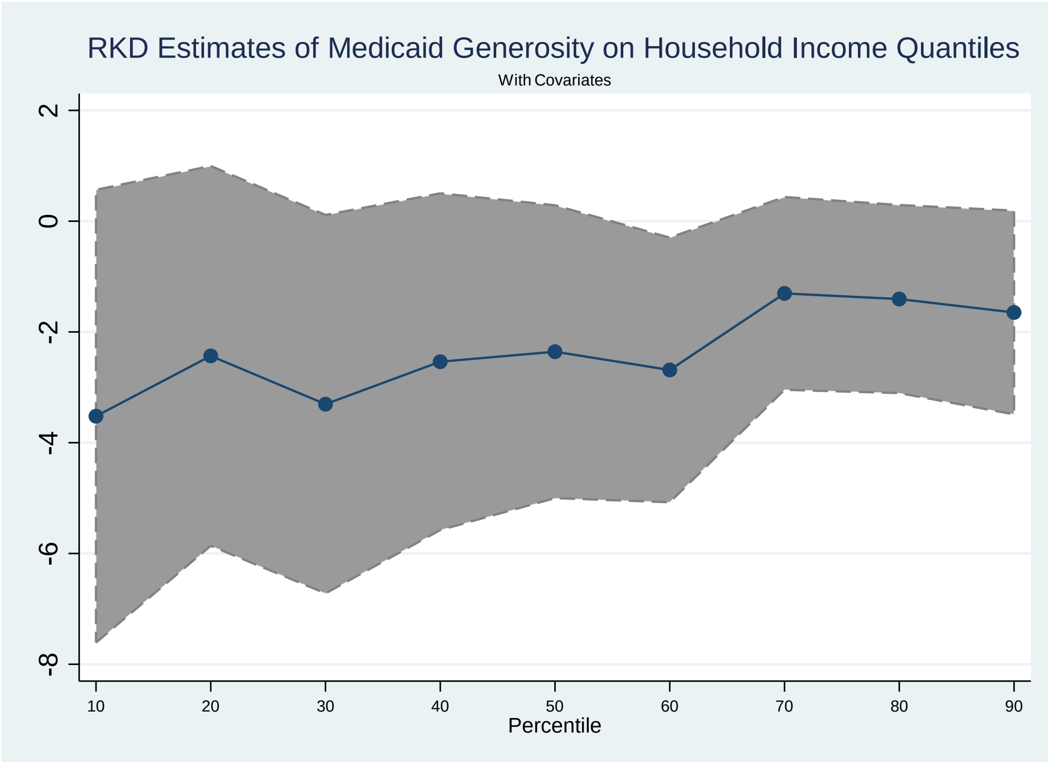
Note: The figure shows binned scatter plots of the upper quantiles of the outcome variable (log real household income) calculate using households with heads 19 years or older from March supplements of IPUMS-CPS. Log real household income is plotted against the running variable—RPCI—normalized relative to the kink point of 1.054, with bin width set to 0.04. The figure shows that the slope of bottom quartile of Log real household income changes abruptly when RPCI *minus* 1.054 (on the horizontal axis) exceeds zero.

Figure 9



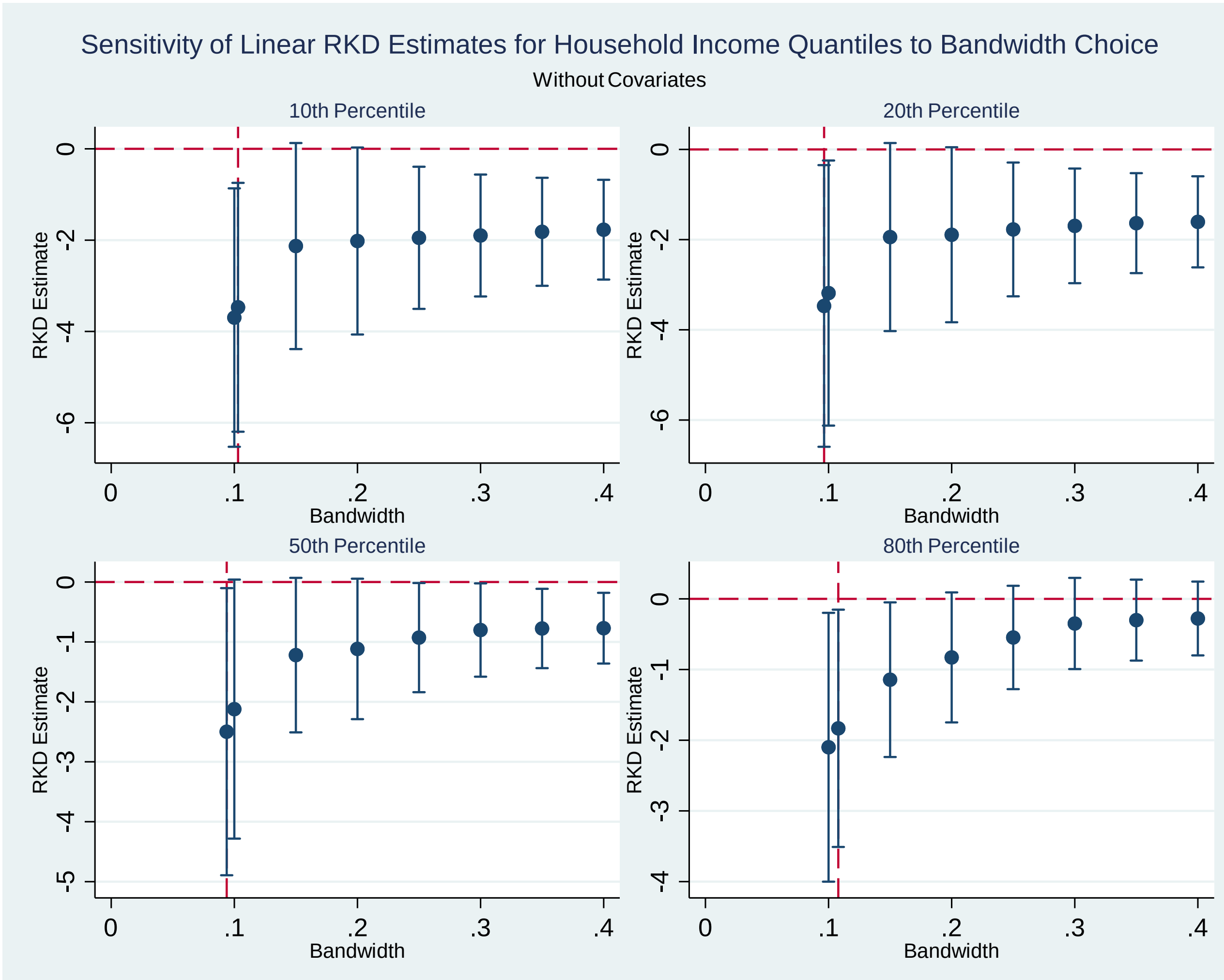
Note: The figure shows fuzzy RKD estimates from local linear regressions of the outcome variable (percentile of log real household income) on the running variable (RPCI). Reduced form estimates normalized by estimated coefficients from local linear regression of the policy variable (FMAP) on the running variable. RKD estimates obtained using rdrobust package from Calonico et. al. (2014b) for the MSE-optimal bandwidth. March CPS-IPUMS data from 1980 to 2013 used to calculate real household income percentiles by state and year. Data on state-year level per-capita personal income from the BEA. Sample restricted to all households with heads 19 years or older. Data on Federal Medical Assistance Percentage (FMAP) are from U.S. Department of Health and Human Services (HHS). See text for other data sources. Confidence intervals are based on standards errors are clustered at the state level.

Figure 10



Note: The figure shows covariate-adjusted fuzzy RKD estimates from local linear regressions of the outcome variable (percentile of log real household income) on the running variable (RPCI). Reduced form estimates normalized by estimated coefficients from local linear regression of the policy variable (FMAP) on the running variable. RKD estimates obtained using rdrobust package from Calonico et. al. (2014b) for the MSE-optimal bandwidth. State-level covariates included: average age, share female, share white, share black, share hispanic, share of high school graduates, share with some college, share with college degree or higher. March CPS-IPUMS data from 1980 to 2013 used to calculate real household income percentiles by state and year. Sample restricted to all households with heads 19 years or older. Data on state-year level per-capita personal income from the BEA. Data on Federal Medical Assistance Percentage (FMAP) are from U.S. Department of Health and Human Services (HHS). See text for other data sources. Confidence intervals are based on standards errors are clustered at the state level.

Figure 11



Note: The figure shows fuzzy RKD estimates from local linear regressions of the outcome variable (percentile of log real household income) on the running variable (RPCI). Reduced form estimates normalized by estimated coefficients from local linear regression of the policy variable (FMAP) on the running variable. RKD estimates obtained using rdrobust package from Calonico et. al. (2014b) for the MSE-optimal bandwidth and the range bandwidths from 0.1 to 0.4 with increments of 0.05. March CPS-IPUMS data from 1980 to 2013 used to calculate real household income percentiles by state and year. Data on state-year level per-capita personal income from the BEA. Sample restricted to all households with heads 19 years or older. Data on Federal Medical Assistance Percentage (FMAP) are from U.S. Department of Health and Human Services (HHS). See text for other data sources. Confidence intervals are based on standards errors are clustered at the state level.

Figure 12

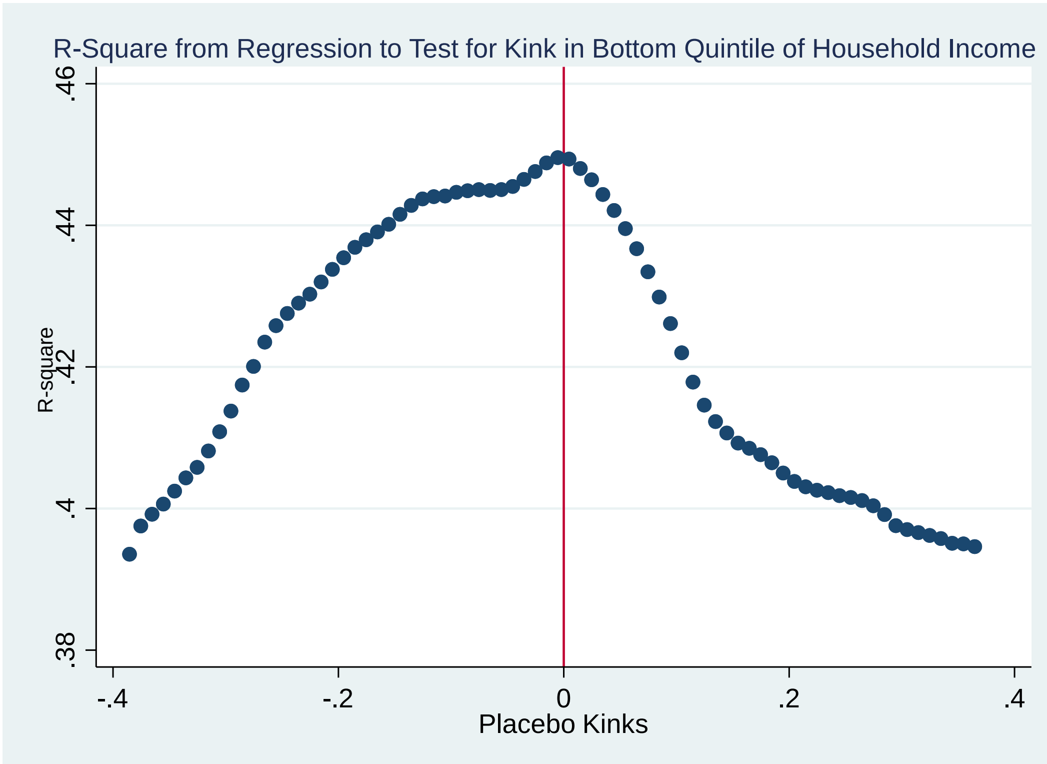
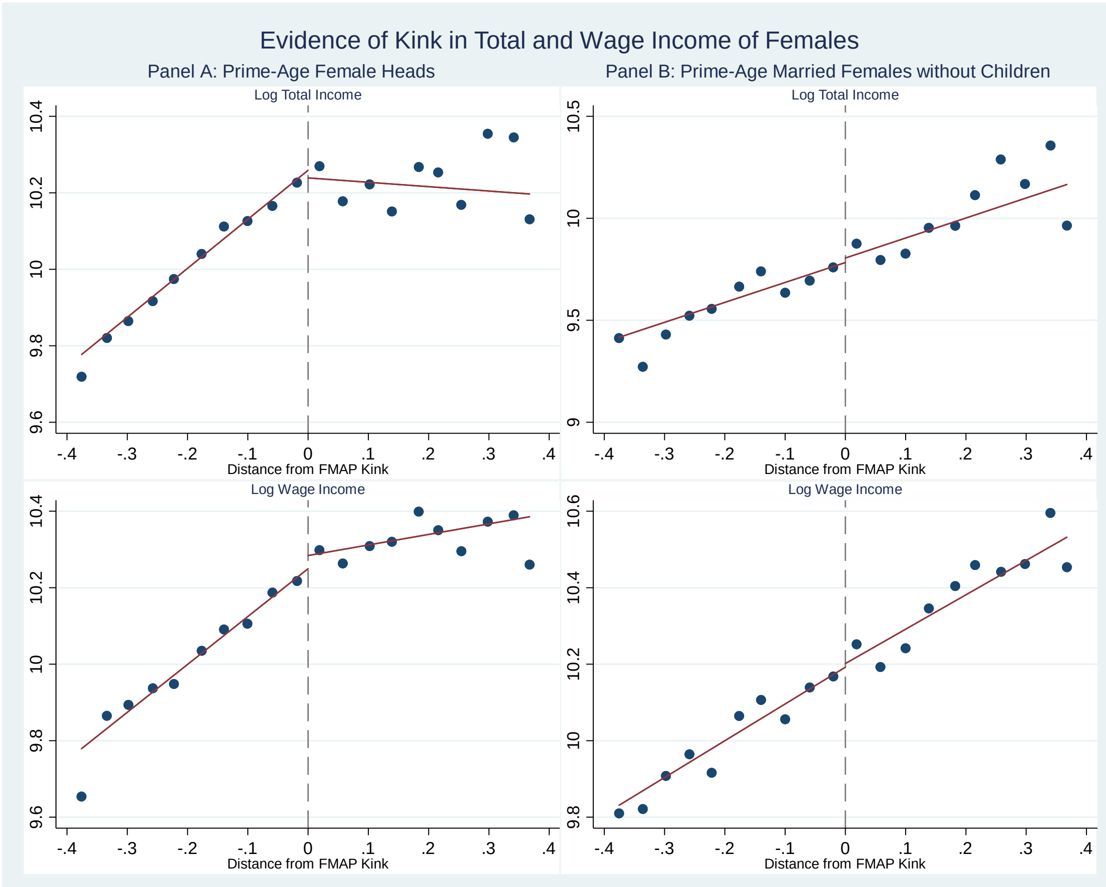
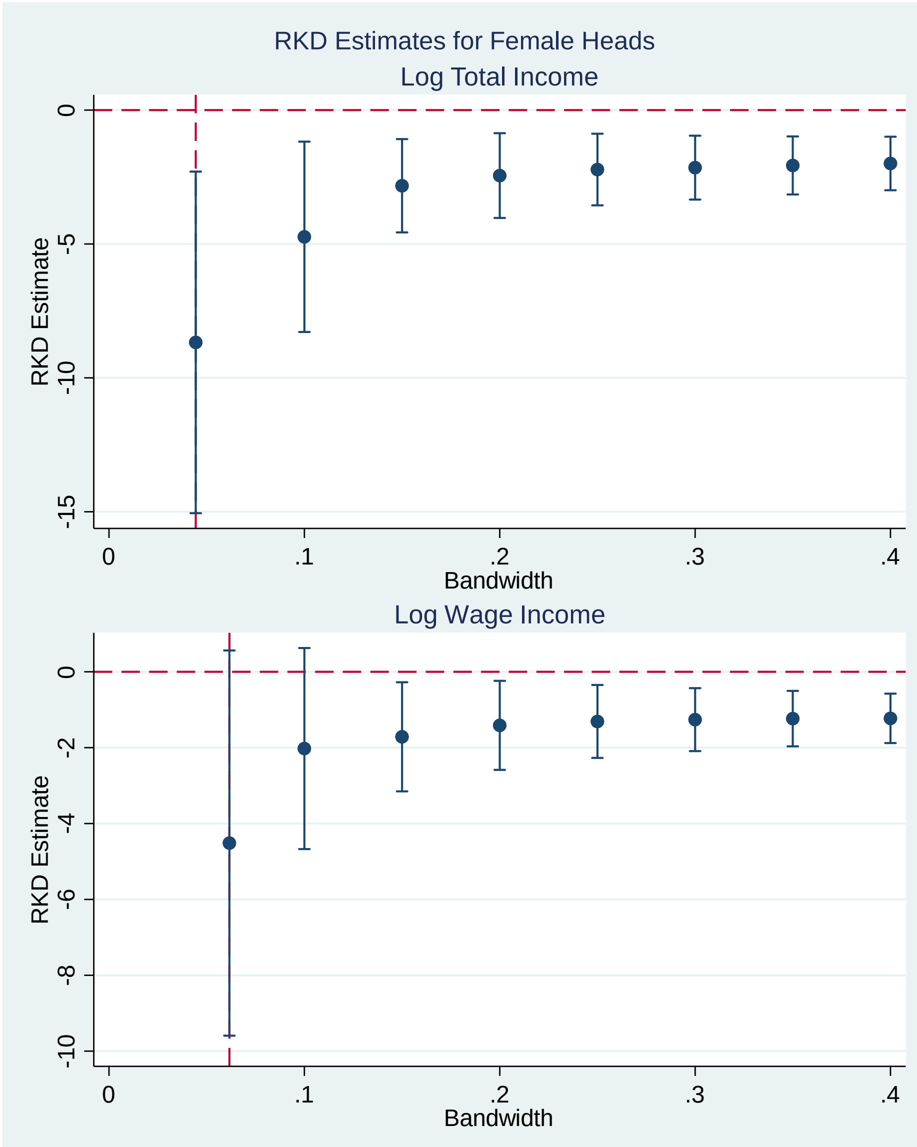

R-Square from Regression to Test for Kink in Bottom Quintile of Household Income
R-square
.38
.4
.42
.44
.46
-.4
-.2
0
.2
.4
Placebo Kinks

Figure 13



Evidence of Kink in Total and Wage Income of Females
Panel A: Prime-Age Female Heads
Panel B: Prime-Age Married Females without Children
Log Total Income
Log Wage Income
Distance from FMAP Kink

Figure 14



The table reports fuzzy RKD estimates from local linear regressions of the outcome variable (log real household income) on the running variable (RPCI), without any other covariates. RKD estimates obtained using rdrobust package from Calonico et. al. (2014b) for the MSE-Optimal bandwidth. March CPS-IPUMS data from 1980 to 2013 used for analysis. Sample restricted to prime-age (22-60 years of age) unmarried female head of households. Data on state-year level per-capita personal income from the BEA. Data on Federal Medical Assistance Percentage (FMAP) are from U.S. Department of Health and Human Services (HHS). Confidence intervals are based on standards errors are clustered at the state level.

Figure 15

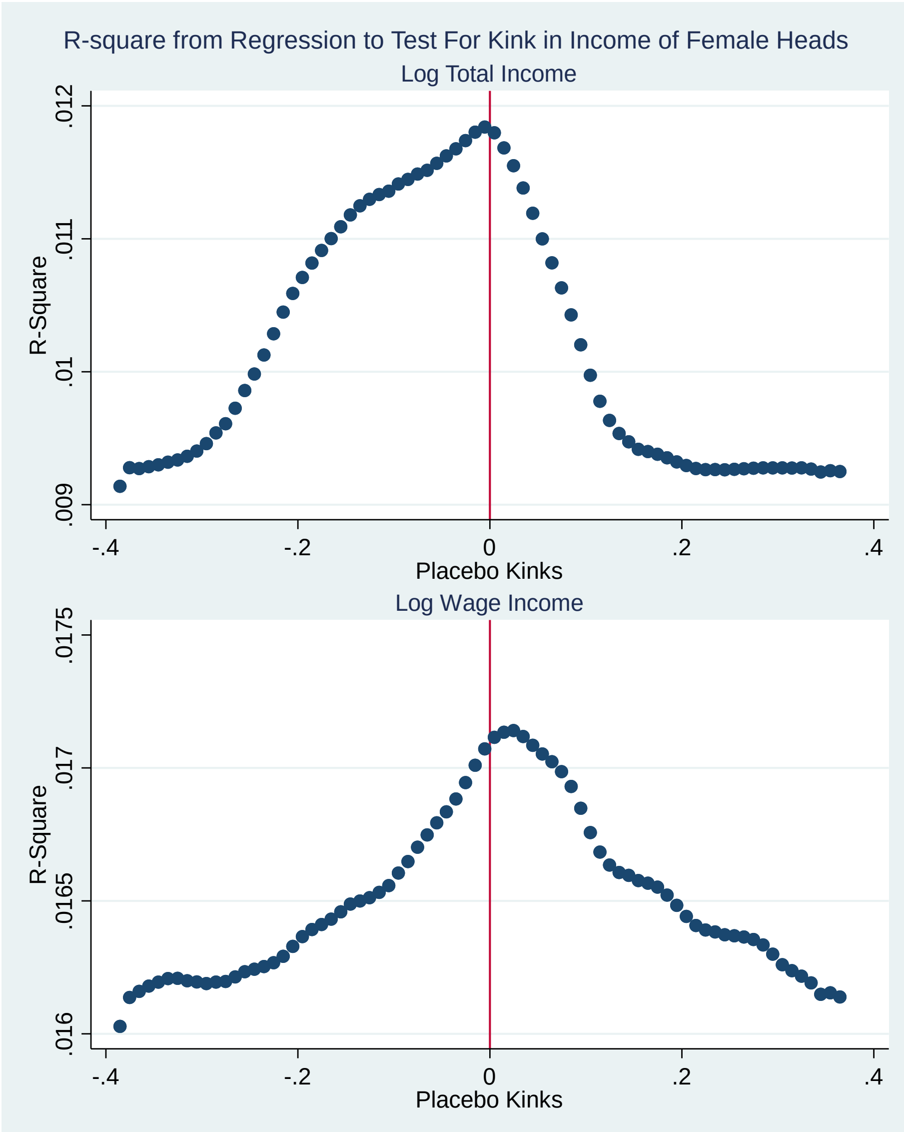

R-square from Regression to Test For Kink in Income of Female Heads
Log Total Income
R-Square
.009
.01
.011
.012
-.4
-.2
0
.2
.4
Placebo Kinks
Log Wage Income
R-Square
.016
.0165
.017
.0175
-.4
-.2
0
.2
.4
Placebo Kinks

Table 1: Tests of Kinks in Covariates at the MSE-Optimal Bandwidth

	Age 19 or older		Single female heads	
	RKD Estimate	P-value	RKD Estimate	P-value
Female	0.428	0.044		
Married	-0.753	0.245		
Age	114.382	0.029	-22.973	0.181
White	2.529	0.492	-0.703	0.828
Black	-0.181	0.81	0.971	0.493
Hispanic	-0.792	0.83	-0.997	0.511
High School	-2.871	0.319	-0.425	0.865
Some College	-1.949	0.136	-3.798	0.022
College Degree	-1.08	0.479	-0.862	0.461
Number of Children	-5.167	0.117	1.077	0.467
State Job Growth Rate	-0.238	0.2	-0.283	0.139
State Unemployment Rate	90.417	0.027	74.983	0.024
State Log House Price	3.921	0.872	-1.197	0.959
State Manufacturing Share	-0.048	0.6	0.026	0.612
State Mining Share	0.892	0.193	0.17	0.51
State Income Tax Rate	-0.128	0.646	-0.212	0.488

Notes: RKD estimates obtained using rdrobust package from Calonico et. al. (2014b) for the MSE-Optimal bandwidth.

Table 2: RKD Estimates of Effect of Medicaid Generosity on Household Income Quantiles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Percentiles	P10	P20	P30	P40	P50	P60	P70	P80	P90
Panel A: Local Linear RKD Without Covariates for MSE-Optimal Bandwidth									
RKD_Estimate	-3.471**	-3.471**	-3.544**	-2.981**	-2.498**	-1.564*	-1.773**	-1.831**	-2.616**
	(1.390)	(1.593)	(1.527)	(1.377)	(1.222)	(0.865)	(0.866)	(0.856)	(1.176)
Observations	1235	1235	1235	1235	1235	1235	1235	1235	1235
Bandwidth	0.10	0.10	0.09	0.09	0.09	0.11	0.11	0.11	0.09
Eff_N_Left	283.00	255.00	235.00	240.00	246.00	318.00	309.00	302.00	246.00
Eff_N_Right	187.00	177.00	169.00	171.00	174.00	199.00	196.00	193.00	174.00
Panel B: Local Linear RKD With Covariates for MSE-Optimal Bandwidth									
RKD_Estimate	-3.522*	-2.433	-3.304*	-2.537	-2.357*	-2.686**	-1.304	-1.406	-1.648*
	(2.086)	(1.750)	(1.743)	(1.551)	(1.349)	(1.219)	(0.888)	(0.866)	(0.939)
Observations	1235	1235	1235	1235	1235	1235	1235	1235	1235
Bandwidth	0.07	0.07	0.06	0.06	0.06	0.06	0.08	0.07	0.07
Eff_N_Left	170.00	193.00	160.00	168.00	159.00	156.00	203.00	177.00	177.00
Eff_N_Right	143.00	149.00	139.00	141.00	139.00	137.00	150.00	145.00	145.00

Notes: * $p<0.10$, ** $p<0.05$. Standard errors in parentheses. Standards errors are clustered at the state level. The figure shows fuzzy RKD estimates from local linear regressions of the outcome variable (percentile of log real household income) on the running variable (RPCI). Reduced form estimates normalized by estimated coefficients from local linear regression of the policy variable (FMAP) on the running variable. RKD estimates obtained using rdrobust package from Calonico et. al. (2014b) for the MSE-optimal bandwidth. March CPS-IPUMS data from 1980 to 2013 used to calculate real household income percentiles by state and year. Sample restricted to all households with heads 19 years or older. Data on state-year level per-capita personal income from the BEA. Data on Federal Medical Assistance Percentage (FMAP) are from U.S. Department of Health and Human Services (HHS). State-level covariates included: average age, share female, share white, share black, share hispanic, share of high school graduates, share with some college, share with college degree or higher.

Table 3: RKD Estimates of Effect of Medicaid Generosity on Household Income Quantiles

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Percentiles	P10	P20	P30	P40	P50	P60	P70	P80	P90
Panel A: Local Quadratic RKD Without Covariates for MSE-Optimal Bandwidth									
RKD_Estimate	-11.675*	-11.323	-7.802*	-5.635*	-5.704*	-5.857	-5.701	-5.430	-5.513
	(6.569)	(7.130)	(4.223)	(3.270)	(3.430)	(3.632)	(3.638)	(3.600)	(3.915)
Observations	1235	1235	1235	1235	1235	1235	1235	1235	1235
Bandwidth	0.09	0.10	0.12	0.13	0.12	0.12	0.12	0.12	0.11
Eff_N_Left	246.00	259.00	343.00	388.00	353.00	343.00	340.00	334.00	330.00
Eff_N_Right	176.00	177.00	208.00	224.00	214.00	208.00	207.00	206.00	203.00
Panel B: Local Quadratic RKD With Covariates for MSE-Optimal Bandwidth									
RKD_Estimate	-6.236*	-5.903*	-5.125*	-4.480*	-3.823*	-4.379*	-4.512*	-3.563*	-0.193
	(3.697)	(3.322)	(2.890)	(2.504)	(2.295)	(2.366)	(2.390)	(1.874)	(1.332)
Observations	1235	1235	1235	1235	1235	1235	1235	1235	1235
Bandwidth	0.08	0.07	0.08	0.08	0.08	0.08	0.09	0.10	0.14
Eff_N_Left	195.00	191.00	201.00	195.00	216.00	204.00	249.00	269.00	451.00
Eff_N_Right	150.00	149.00	150.00	150.00	161.00	152.00	176.00	179.00	236.00

Notes: * $p<0.10$, ** $p<0.05$. Standard errors in parentheses. Standards errors are clustered at the state level. The table shows fuzzy RKD estimates from local quadratic regressions of the outcome variable (percentile of log real household income) on the running variable (RPCI). Reduced form estimates normalized by estimated coefficients from local linear regression of the policy variable (FMAP) on the running variable. RKD estimates obtained using rdrobust package from Calonico et. al. (2014b) for the MSE-optimal bandwidth. March CPS-IPUMS data from 1980 to 2013 used to calculate real household income percentiles by state and year. Sample restricted to all households with heads 19 years or older. Data on state-year level per-capita personal income from the BEA. Data on Federal Medical Assistance Percentage (FMAP) are from U.S. Department of Health and Human Services (HHS). State-level covariates included: average age, share female, share white, share black, share hispanic, share of high school graduates, share with some college, share with college degree or higher.

Table 4: RKD Estimates of the Effect of Medicaid Generosity on Female Heads

	(1) Log Total Income	(2) Log Wage Income	(3) Log Non-wage Income
Panel A: Local Linear RKD Without Covariates for MSE-Optimal Bandwidth			
RKD_Estimate	-8.675**	-4.515*	0.207
	(3.254)	(2.590)	(4.920)
Observations	160146	126381	124630
Bandwidth	0.04	0.06	0.06
Eff_N_Left	14142.00	18907.00	18517.00
Eff_N_Right	20861.00	18571.00	18337.00
Panel B: Local Linear RKD With Covariates for MSE-Optimal Bandwidth			
RKD_Estimate	-4.321*	-2.809	-1.365
	(2.312)	(2.255)	(3.722)
Observations	160146	126381	124630
Bandwidth	0.05	0.04	0.06
Eff_N_Left	15425.00	10261.00	18777.00
Eff_N_Right	21598.00	16128.00	18373.00

Notes: * $p<0.10$, ** $p<0.05$. Standard errors in parentheses. Standards errors are clustered at the state level. The figure shows fuzzy RKD estimates from local linear regressions of the outcome variable (log real household income) on the running variable (RPCI). RKD estimates obtained using rdrobust package from Calonico et. al. (2014b) for the MSE-Optimal bandwidth. Covariates included in panel B: age, dummies for white, black, and hispanic, high school graduate, some college, college degree or higher, and number of children. March CPS-IPUMS data from 1980 to 2013 used for analysis. Sample restricted to prime-age (22-60 years of age) unmarried female head of households. Data on state-year level per-capita personal income from the BEA. Data on Federal Medical Assistance Percentage (FMAP) are from U.S. Department of Health and Human Services (HHS).

Table 5: RKD Estimates of the Effect of Medicaid Generosity on Female Heads

	(1) Log Total Income	(2) Log Wage Income	(3) Log Non-wage Income
Panel A: Local Quadratic RKD Without Covariates for MSE-Optimal Bandwidth			
RKD_Estimate	-11.244**	-8.036	-6.427
	(5.429)	(6.031)	(7.886)
Observations	160146	126381	124630
Bandwidth	0.07	0.08	0.07
Eff_N_Left	25947.00	24614.00	21353.00
Eff_N_Right	24681.00	20364.00	19624.00
Panel B: Local Quadratic RKD With Covariates for MSE-Optimal Bandwidth			
RKD_Estimate	-8.436*	-5.726	-7.142
	(4.751)	(4.085)	(7.174)
Observations	160146	126381	124630
Bandwidth	0.07	0.07	0.07
Eff_N_Left	24151.00	21202.00	20900.00
Eff_N_Right	24060.00	19407.00	19207.00

Notes: * $p<0.10$, ** $p<0.05$. Standard errors in parentheses. Standards errors are clustered at the state level. The table reports fuzzy RKD estimates from local quadratic regressions of the outcome variable (log real household income) on the running variable (RPCI). RKD estimates obtained using rdrobust package from Calonico et. al. (2014b) for the MSE-Optimal bandwidth. Covariates included in panel B: age, dummies for white, black, and hispanic, high school graduate, some college, college degree or higher, and number of children. March CPS-IPUMS data from 1980 to 2013 used for analysis. Sample restricted to prime-age (22-60 years of age) unmarried female head of households. Data on state-year level per-capita personal income from the BEA. Data on Federal Medical Assistance Percentage (FMAP) are from U.S. Department of Health and Human Services (HHS).

Appendix

Table A1: Summary Statistics

	Bandwidth (0.1)		Bandwidth (0.2)		All	
	Below Kink	Above Kink	Below Kink	Above Kink	Below Kink	Above Kink
Log HH Income	10.98	11.07	10.95	11.07	10.91	11.09
	(0.898)	(0.917)	(0.906)	(0.930)	(0.912)	(0.933)
Female	0.519	0.515	0.519	0.519	0.521	0.519
	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)	(0.500)
Married	0.590	0.572	0.592	0.563	0.596	0.563
	(0.492)	(0.495)	(0.491)	(0.496)	(0.491)	(0.496)
Age	45.85	44.56	45.55	44.81	45.52	44.98
	(17.70)	(17.18)	(17.52)	(17.30)	(17.52)	(17.31)
White	0.777	0.658	0.757	0.673	0.757	0.678
	(0.416)	(0.475)	(0.429)	(0.469)	(0.429)	(0.467)
Black	0.0873	0.0942	0.103	0.105	0.113	0.105
	(0.282)	(0.292)	(0.304)	(0.307)	(0.317)	(0.306)
Hispanic	0.0881	0.160	0.0962	0.142	0.0855	0.139
	(0.0865)	(0.114)	(0.107)	(0.1000)	(0.106)	(0.0966)
High School	0.246	0.201	0.263	0.214	0.260	0.223
	(0.431)	(0.401)	(0.440)	(0.410)	(0.438)	(0.416)
Some College	0.249	0.262	0.255	0.252	0.252	0.250
	(0.433)	(0.439)	(0.436)	(0.434)	(0.434)	(0.433)
College +	0.226	0.254	0.221	0.260	0.213	0.266
	(0.418)	(0.436)	(0.415)	(0.439)	(0.409)	(0.442)
Children	0.763	0.811	0.773	0.800	0.778	0.798
	(1.113)	(1.152)	(1.114)	(1.138)	(1.117)	(1.132)
State Job Growth	0.0162	0.0141	0.0174	0.0125	0.0175	0.0120
	(0.0195)	(0.0158)	(0.0184)	(0.0166)	(0.0180)	(0.0163)
State Unem Rate	5.866	6.288	5.797	6.145	5.886	6.106
	(1.714)	(1.806)	(1.615)	(1.693)	(1.645)	(1.692)
Ln House Price Ind	5.316	5.536	5.284	5.594	5.258	5.623

	(0.411)	(0.468)	(0.377)	(0.490)	(0.377)	(0.490)
GDP Share Manfg.	0.161	0.142	0.176	0.132	0.179	0.132
	(0.0744)	(0.0392)	(0.0690)	(0.0445)	(0.0681)	(0.0434)
GDP Share mining	0.0114	0.00755	0.0221	0.00598	0.0260	0.00548
	(0.0257)	(0.0191)	(0.0422)	(0.0160)	(0.0454)	(0.0153)
State Tax by PI	0.0164	0.0248	0.0166	0.0268	0.0172	0.0266
	(0.0127)	(0.00972)	(0.0124)	(0.00969)	(0.0116)	(0.00946)

Notes: The table reports sample means, with standard deviations in parenthesis. Sample restricted to all individuals 19 years and older in March supplements of IPUMS-CPS from 1980-2013, with some exclusions, as detailed in section 3 on data and summary statistics.

Table A2: Robustness of RKD Estimates of the Effect of Medicaid Generosity on Lower Quantiles of Household Income Distribution

	(1)	(2)	(3)	(4)	(5)
Panel A: MSE-Optimal Bandwidth					
10^{th} Percentile	-4.393**	-3.411	-1.102*	-0.612	-0.296
	(2.015)	(2.402)	(0.630)	(0.416)	(0.482)
20^{th} Percentile	-3.115*	-3.375	-1.000*	-0.686**	-0.437
	(1.725)	(2.611)	(0.562)	(0.322)	(0.435)
25^{th} Percentile	-7.331*	-3.000	-0.940*	-0.676**	-0.380
	(4.210)	(1.985)	(0.521)	(0.318)	(0.377)
Observations	370	237	872	872	872
Bandwidth $^{\xi}$	0.08	0.05	0.20 $^{\Psi}$	0.20 $^{\Psi}$	0.20 $^{\Psi}$
R-Sq$^{¥}$	.	0.37	0.59	0.81	0.84
Panel B: Full Sample					
10^{th} Percentile	-1.722**	-0.830**	-0.819**	-0.799**	-0.486
	(0.496)	(0.386)	(0.336)	(0.305)	(0.369)
20^{th} Percentile	-1.576**	-0.768**	-0.761**	-0.918**	-0.538
	(0.455)	(0.376)	(0.321)	(0.254)	(0.379)
25^{th} Percentile	-1.449**	-0.729**	-0.728**	-0.911**	-0.483
	(0.410)	(0.348)	(0.296)	(0.245)	(0.322)
Covariates	No	Yes	Yes	Yes	Yes
Year Effects	No	No	Yes	Yes	Yes
State Effects	No	No	No	Yes	Yes
State X trend	No	No	No	No	Yes
Observations	1235	1235	1235	1235	1235
Bandwidth	0.40	0.40	0.40	0.40	0.40
R-Sq$^{¥}$	0.41	0.66	0.74	0.88	0.90

Notes: Fuzzy RKD estimates obtained using simple 2SLS procedure. See notes to Table 2 for other details. $^{\xi}$ MSE-optimal bandwidth reported is for the 10^{th} and 20^{th} percentiles. For 25^{th} percentile, it changed to 0.06 and 0.05 in columns (1) and (2), respectively. $^{\Psi}$ Bandwidths set to 0.2 because MSE-optimal bandwidth procedure failed due to too many covariates. $^{¥}$ R-squares reported are for the 20^{th} percentile.