JOURNAL OF APPLIED ECONOMETRICS
J. Appl. Econ. **24**: 282–308 (2009)
Published online 12 November 2008 in Wiley InterScience
(www.interscience.wiley.com) DOI: 10.1002/jae.1039

PUBLIC INSURANCE AND PRIVATE SAVINGS: WHO IS AFFECTED AND BY HOW MUCH?

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SUMMARY

This paper employs a recently developed instrumental quantile regression method to investigate the effect of Medicaid on household savings across different wealth groups. It finds that the disincentive effect of Medicaid on household savings is heavily concentrated in the middle net-worth households. In contrast, the effects on the bottom and top net-worth households are quite small and insignificant. These heterogeneous incentive effects are partly explained by Medicaid asset tests. Our findings hold regardless of whether affluence is measured in terms of wealth or income. They suggest that despite generating substantial crowd-out for the mean household, Medicaid expansions are unlikely to discourage the savings of the poorest households.

1. INTRODUCTION

A central question concerning public insurance programs is the extent to which they crowd out private savings. Government insurance plans, such as Medicaid or Aid to Families with Dependent Children (AFDC), may crowd out savings in two primary ways. First, by insuring households against out-of-pocket medical expenses or income shocks, public insurance programs may reduce the household's reliance on precautionary savings as an alternative form of insurance, as suggested by the simulation results in Kotlikoff (1989). Secondly, as demonstrated by Hubbard *et al*. (1995), asset test eligibility requirements act as an implicit tax on wealth and may encourage households to spend down assets in order to qualify for public insurance programs.[1]

The effect of public insurance on private savings has been an active area of empirical research (e.g., Starr-McCluer, 1996; Palumbo, 1999; Chou *et al*., 2003; Powers, 1998). Using the quasi-exogenous component of the variation from the expansion of Medicaid coverage, Gruber and Yelowitz (1999) find empirical support for the contention that, on average, an increase in a household's Medicaid coverage leads to a reduction in household wealth and that this effect is magnified in the presence of an asset test. A recent study by Hurst and Ziliak (2006) uses the 1996 Welfare reform to test whether welfare asset limits serve as a deterrent to savings for poor households. Interestingly, they find no effect of the welfare policy changes, which relaxed asset

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[1] Since public insurance programs provide an in-kind transfer payment, the associated wealth effect provides a third channel whereby public insurance may affect savings.

test limits, on the savings of female-headed households with children, a demographic group which tends to be at risk of taking up welfare and thus would seem likely to respond to the policy reform.

The fact that the savings effect of public insurance may vary across households of different wealth or income levels is suggested by the theoretical contributions of Hubbard *et al*. (1995), who argue that public insurance, in combination with an asset test, provides stronger savings disincentives to low-than to high-income households. They use this heterogeneity to explain the sharp and rather puzzling disparity of savings rates observed across wealth and income groups. Most of the public insurance programs, such as Medicaid and AFDC, were originally designed as safety nets for poor households. Savings rates among these groups are already quite low. Thus, although the welfare implications are uncertain,[2] to the extent that the savings crowd-out is concentrated among poor households, this may be of particular concern to policy makers. As Sherraden (1991) argues, savings are of crucial importance to the long-run economic status of poor households. With limited ability to borrow, a lack of savings may force these households to forgo important investments in education or down payments on home or business ownership. Ultimately, this may make it more difficult for the family, as well as their offspring, to exit from poverty.

Therefore, both economic and policy considerations suggest the importance of examining the disincentive effects of public insurance programs across different segments of the wealth distribution. Employing the data on the expansion of Medicaid in the late 1980s/early 1990s that Gruber and Yelowitz (1999) use to study population average effects, we ask whose savings are affected by Medicaid and by how much. Specifically, we investigate the effect of Medicaid on savings across households with different wealth levels, using a recently developed instrumental variable quantile regression approach. In this way, we can directly measure the savings effect of Medicaid on the poorest households, who make the greatest use of Medicaid and whose savings are lowest. Moreover, this allows us to assess the empirical predictions of Hubbard *et al*. (1995) on the differential effect of Medicaid asset tests across households of different means.

Our study yields interesting empirical results. We find a strong negative impact of Medicaid coverage on median household wealth. We also find that the effect dissipates as we move into the top quantiles and becomes insignificant in the top decile. This is an expected result that follows the prediction of Hubbard *et al*. (1995). In fact, if the results for the upper quantiles hold any surprise, it is rather that response does not dissipate more quickly. Perhaps most interestingly, the effect again dissipates in the lower quantiles. In fact, for the poorest households, who have the highest participation rates in Medicaid, there is no evidence that Medicaid has any impact whatsoever on household asset accumulation. As we argue below, this could be due to the fact that the net worth of the poorest households lies safely below asset test thresholds and their consumption–savings choices may also be restrained by credit constraints.

We explore the explanation behind the heterogeneous savings effects uncovered here. The differential impact of asset testing across net worth quantiles is found to be an important component to this explanation. Like Medicaid spending itself, we find that Medicaid asset tests also have no effect on the top and bottom net worth quantiles. The effect is strongest for the lower middle quantiles. For these households, asset levels tend to be only a few thousand dollars above the eligibility ceilings. Thus, any policy or family structure change that leads them to become eligible on other grounds creates a strong savings disincentive in order to meet the asset test. By contrast,

[2] Unlike the savings reductions due to Medicaid asset tests, reductions in precautionary savings may not cause distortions, as precautionary saving is itself an inefficient form of savings.

DOI: 10.1002/jae

households in the top quantiles would have to spend down substantial assets in order to qualify for Medicaid. As argued by Hubbard *et al*. (1995), they are unlikely to find this an attractive option. Finally, the households in the bottom quantiles have few savings to begin with and thus qualify automatically on asset test grounds, without any need to further reduce their asset holdings.

Nevertheless, we find that the differential incentives caused by asset testing can explain only part of the overall heterogeneity in the savings response to Medicaid. Even in the absence of an asset test, the effect of Medicaid on savings still varies considerably across quantiles. This suggests that the strength of a household's precautionary savings response to Medicaid also depends on its wealth level. In particular, households in the middle quantiles may have substantial precautionary savings reserved for use in the event of a medical emergency, prior to their enrollment in Medicaid. After meeting eligibility requirements, such precautionary savings may no longer be necessary, suggesting a sharp drop in net assets. By contrast, the very poorest households have little to no precautionary savings, regardless of whether they are eligible for Medicaid. Medical emergencies often entail large discrete costs, such as hospital stays, and, with limited economic opportunities, many of these households may have little prospect of accumulating sufficient net worth to provide useful levels of precautionary medical savings in the absence of Medicaid. Similarly, they may not be able to increase consumption much in the presence of Medicaid due to credit constraints.

In the quantile regression results discussed above, poverty is implicitly defined in terms of net worth. However, it is possible that some households may have high incomes but few assets or vice versa. Examples would include newly minted doctors or lawyers with high starting salaries but large student loans or a head of household facing a long stretch of unemployment after many years of high salary and savings. Therefore, we also examine the savings disincentive effects of Medicaid and asset testing across the quantiles of labor income. This analysis indicates that Medicaid has no effect on the bottom and top 20% of households as measured by labor income. Therefore, the same general conclusions hold regardless of whether we define poverty in terms of assets or income.

Our findings have several important implications. Medicaid has traditionally targeted poor households, for whom savings rates are quite low. Although the welfare effects are uncertain, any tendency to further crowd out these already low savings may still be of concern in a program designed to address poverty. Yet, we find no evidence to suggest that Medicaid discourages savings among the poorest households. Thus, among this demographic, any *ex ante* Medicaid savings disincentives for healthy households appear second order relative to the *ex post* benefits associated with Medicaid coverage for households with disability or long-term illness.

Secondly, our findings potentially reconcile some of the results of the previous literature. For example, focusing on female-headed households with children, a disproportionately poor population, Hurst and Ziliak (2006) find no evidence that asset tests affect savings, whereas Gruber and Yelowitz (1999) find evidence of a strong effect when averaged across the positive net worth Survey of Income and Program Participation (SIPP) population. Our results, which find no savings effects for households towards the bottom of the wealth distribution, yet strong effects for the median household, are consistent with the findings of both studies. More generally, this suggests that the conclusions obtained from population average studies may show some sensitivity to the income and/or wealth composition of the sample employed. In fact, when controlling for labor income, we also find that both the estimate and significance of the mean savings response in the SIPP is sensitive to the inclusion of non-positive net worth households.

Our study also sheds some light on the ability of public insurance programs to explain the puzzling low savings rates among the poorest households. Standard consumption smoothing models tend to have difficulty explaining the difference in savings rates between low-and high-income households. This suggests that heterogeneity of some form is likely important in resolving this puzzle. Public insurance programs, which are relevant to poor, but not to wealthy households, thus provide a promising explanation (Hubbard *et al.*, 1995). Our results are supportive of this explanation in so far as it applies to the moderately poor households in the lower middle net worth quantiles. On the other hand, we do not find any evidence that public insurance helps to explain the abnormally low savings rates found among the very poorest households. Simply put, these households do not appear to maintain any significant savings, regardless of whether or not they are on Medicaid.

Finally, our results imply that the percentage savings response to a one-dollar increase in Medicaid for a household in the eighth net worth decile is approximately the same as that of a household in the third decile. This comparison is particularly stark when measured in dollar savings responses, but seems somewhat less severe when viewed as elasticities. To the extent that the estimated saving disincentive effects in the upper-middle deciles (6–8) seem large relative to prior beliefs, they may suggest some caution regarding the empirical specification and therefore the causal inference that Medicaid affects savings.[3] We discuss this caveat further in Section 3.2.

The rest of the paper proceeds as follows. Section 2 describes the data and methodology. Section 3 presents and explains the empirical results, and Section 4 summarizes and concludes.

2. DATA AND METHODOLOGY

2.1. Data

In this study, we employ data from the Survey of Income and Program Participation (SIPP), spanning 1984–1993. The SIPP consists of a series of overlapping panels initiated on a yearly basis, but lasting for a total of 24–32 months, during which time the same households are repeatedly interviewed at 4-month intervals in order to collect data on household income and Medicaid participation.

Data on household net worth was collected from each household as part of a special topical module. Net worth is defined as the sum of financial assets and home, vehicle, and business equity, net of debt. In the SIPP database, assets are defined to include interest-earning assets,[4] stocks and mutual fund shares, mortgages held from the sale of real estate, amount due from sale of business or property, regular checking accounts, US Savings Bonds, real estate, IRAs and KEOGH accounts, and motor vehicles. Debts include both secured debt (mortgages, business or professional debt, vehicle loans, and margin and broker accounts) and unsecured debt (credit card and store bills, medical bills, educational loans, and loans from individuals and financial institutions).

Following Gruber and Yelowitz (1999), we employ the wealth information for each household from the special topical module, together with an average of the other household characteristics obtained from the interviews for that household prior to and including the wealth module. Thus,

[3] We thank an anonymous referee for pointing this out.

[4] These include passbook savings accounts, money market funds, deposit accounts, certificates of deposit, interest earning checking accounts, US government securities, and municipal and corporate bonds.

DOI: 10.1002/jae

we employ a pooled cross-section with one observation for each household, spanning 10 years and 52,706 households, of which 40,442 have positive net worth.[5,6]

This is a particularly interesting period in which to study the effects of Medicaid. Prior to 1984, Medicaid had strict income and asset requirements, and was limited to female-headed households receiving welfare benefits through the Aid to Families with Dependent Children (AFDC) program. However, over the next decade, Medicaid underwent a number of expansions, which relaxed family structure, income, and asset eligibility requirements. This policy change was the result of separate legislative changes passed and implemented over several years and thus provides substantial variability in Medicaid benefits across the time series dimension of the data. Although the changes occurred at the federal level, the legislation left the states considerable flexibility as to the speed and, to some extent, the depth of the expansion. States also varied widely according to the age cut-off for children's eligibility. Therefore, these changes also gave rise to considerable variability across states. More importantly for our study, even within the same state and year, the value of the eligibility expansion varied considerably across households, depending on the household family structure, age, and the local cost of medical services. The reader is referred to Gruber and Yelowitz (1999) and Currie and Gruber (1996a,b) for a detailed account of these expansions.

2.2. Methodology

Our primary interest lies in the response of household net worth to changes in the value of the Medicaid subsidy, which reflect changes to both Medicaid eligibility and generosity. The dependent variable, net worth, is directly available from SIPP. The primary regressor, Medicaid eligible dollars (MED), is a carefully constructed measure of the household's expected Medicaid subsidy proposed by Gruber and Yelowitz (1999) and Currie and Gruber (1996a,b). This measure takes into account variation at the household level in both the probability of Medicaid eligibility (due to differences in family structure, income, assets, and eligibility requirements) and expected health care costs (as a function of family composition, age, and state-specific medical costs). The full value of Medicaid to a household includes its value in both current and future years. The expected Medicaid benefit for family j in year t with family members indexed by i is therefore defined as the discounted sum of expected future Medicaid benefits:[7]

$$\mathrm{MED}_{j,t} = \sum_{s=0}^{\infty}(1+r)^{-s}\sum_{i}\mathrm{ELIG}_{i,j,t+s} \times \mathrm{SPEND}_{i,j,t+s} \tag{1}$$

where $\mathrm{ELIG}_{i,j,t+s}$ is the probability in year t that family member i is eligible for Medicaid in year $t+s$, conditional on the continuation of the Medicaid eligibility rules in place in year t, $\mathrm{SPEND}_{i,j,t+s}$ is the expected Medicaid subsidy conditional on eligibility, and r is the real interest rate set to 6%.

[5] Households with imputed net worth (about 1/4 of households) are excluded from the sample on account of the reported problems with this imputation method (Curtin *et al*., 1989; Hurd *et al*., 1998). Likewise, the sample was restricted to heads of household aged 16–64 and a maximum household age of 64, in order to exclude Medicare recipients. Also omitted were households containing more than one family. See Gruber and Yelowitz (1999) for further details.

[6] Note that this pooled cross-section differs from a panel in that different households' wealth information is sampled at different points in time.

[7] Note that the expectations are implicit in the definitions of SPEND and ELIG.

DOI: 10.1002/jae

As discussed above, the large but uneven expansion of Medicaid gives rise to substantial variation in both Medicaid eligibility and the expected value of Medicaid to households. However, this variability must be employed with care since policy changes are not true natural experiments and some of this variation is likely endogenous. One potential source of endogeneity may arise from the effects of lobbying or other political pressures affecting policy. This suggests correlation between policy changes and average yearly household characteristics due to political economy considerations at the federal level, and between policy and average state–year household characteristics due to lobbying at the state level. Therefore, the exogeneity of policy changes across both states, years, and state–year cells is questionable. For this reason, it seems preferable to focus on the within-state–year cell variability in Medicaid eligible dollars. This variation arises from the fact that the same policy change may have substantially different effects on eligibility across households due to the interaction between the policy change and the household characteristics. By including a full set of year, state, and year–state interaction dummy variables to absorb the variation across year–state cells, we follow Gruber and Yelowitz (1999) in employing only this within-cell variation.

A second potential source of endogeneity arises from the fact that eligibility also depends on both wealth levels (via asset tests) and income levels (via income tests), which themselves depend in part on net worth. This suggests that a substantial portion of the variability in eligibility may be endogenous and thus MED requires an instrument. A natural instrument in this context is the exogenous component to Medicaid eligible dollars. This is constructed in Gruber and Yelowitz (1999) as a second measure of expected Medicaid subsidies, simulated Medicaid eligible dollars (SIMMED), in which the probability of eligibility is conditioned on what they argue to be the factors determined exogenously to current savings decisions: education, age, state, and year. To be precise, the probability of eligibility, ELIG in (1), is replaced by SIMELIG, in which this probability is simulated using only the exogenous factors discussed above. Then, the expected Medicaid benefit for family j in year t conditional on exogenous factors only is given by

$$\mathrm{SIMMED}_{j,t} = \sum_{s=0}^{\infty}(1+r)^{-s}\sum_{i}\mathrm{SIMELIG}_{i,j,t+s} \times \mathrm{SPEND}_{i,j,t+s}$$

which is defined in the same way as MED in (1), except that ELIG is replaced by SIMELIG.

To examine the effect of Medicaid across different segments of wealth distribution, we employ a quantile regression approach, which allows us to estimate the marginal effect of a given Medicaid expansion for households at different points in the conditional wealth distribution. This makes it possible to separately assess the implication of Medicaid reform for poor, middle-class, and wealthy households. Since Medicaid eligible dollars requires an instrument, we employ the instrumental variable quantile regression approach of Chernozhukov and Hansen (2004b, 2005). This method, which we briefly describe in the following section, provides one of several recent solutions to the long-standing problem of quantile regression with endogenous regressors.[8]

Accordingly, the baseline specification consists of an instrumental quantile regression of log net worth on Medicaid eligible dollars, together with a large number of control variates to account

[8] See also Powell (1983), Chen and Portnoy (1996), Alberto *et al*. (2002), Chesher (2003), Ma and Koenker (2006), Chernozhukov and Hansen (2006), and Horowitz and Lee (2007) for alternative solutions to related problems involving endogeneities in quantile regression.

DOI: 10.1002/jae

for the other factors that enter the savings decision. These include state, year, and state–year interaction dummy variables and controls for education, family demographic structure and other household covariates.

2.3. Instrumental Quantile Regression

2.3.1 Quantile Regression

The quantile regression, introduced by Koenker and Bassett (1978), estimates the τ quantile, $Q_Y(\tau|x)$, of Y, conditional on $X = x$, where $\tau\varepsilon(0, 1)$ indexes the quantile level and where capital letters denote random variables and lower-case letters denote their realizations. In a linear quantile regression model, this is specified as $Q_Y(\tau|x) = x'\gamma(\tau)$. Under the asymmetric absolute deviation loss function $\rho_\tau(u) = u(\tau - 1(u < 0))$, Koenker and Bassett (1978) show that the expected loss is minimized by the conditional quantile $Q_Y(\tau|x)$. The quantile regression coefficients $\hat{\gamma}(\tau)$ are then chosen to minimize the finite sample analog $\frac{1}{n}\sum_{i=1}^{n}\rho_\tau(Y_i - X_i'\gamma)$. For example, $\rho_{1/2}(u) = 1/2|u|$ is used for Laplace's median regression function.

The quantile regression is robust to the outliers that are often present in data on wealth. Most importantly for our study, it offers a rich description of the manner in which the regressors influence the dependent variable. Rather than restricting the influence of X to shifts in the conditional mean of Y, it allows for differential effects of X at different points in the distribution of Y. This is because the coefficients $\gamma(\tau)$ are allowed to vary in a flexible manner according to the quantile level τ. In particular, a linear quantile regression estimates the model

$$Y = X'\gamma(U) \tag{2}$$

where

$$U|X \sim \text{Uniform(0,1)} \tag{3}$$

and $Q_y(\tau|x) = x'\gamma(\tau)$ is by design the τ quantile of Y conditional on $X = x$. This provides a flexible description of the conditional distribution function.

In contrast, the standard regression model with homoscedastic errors restricts the influence of the regressors to parallel shifts in the distribution function, in which they have the same influence across the entire distribution. In the current context, standard regression assumptions require Medicaid to have the same expected impact on the wealthiest household in the sample as on the poorest, whereas quantile regression allows us to estimate the impact on the wealthy separately from the impact on the poor.

2.3.2 Instrumental Quantile Regression

When its econometric assumptions are satisfied, the model in (2)–(3) provides a causal interpretation for the quantile coefficients $\gamma(\tau)$, which represent the effect of a one-unit change in the regressor on the τ quantile of Y. The key identifying assumption underlying this interpretation is the condition in (3) requiring the error term U to be independent of X. When one or more of the regressors is endogenous, this condition is violated. While the conditional quantile function can then still be estimated as a descriptive statistic, it loses its causal interpretation. This is the case in the current study since, as discussed above, Medicaid eligible dollars are endogenous and require an instrument.

DOI: 10.1002/jae

We therefore employ the instrumental quantile regression of Chernozhukov and Hansen (2004b, 2005). Denoting the endogenous regressors by D, the included exogenous regressors by X, and the excluded exogenous instruments by Z, we estimate the structural quantile regression model:[9]

$$Y = D'\alpha(U) + X'\beta(U) \tag{4}$$

$$U|X, Z \sim \text{Uniform(0,1)} \tag{5}$$

$$D = \delta(X, Z, V) \tag{6}$$

The identifying assumption in (5) requires that U be independent of both X and Z, but there is no restriction on the dependence between U and V, the potentially endogenous component to D.

The interpretation of coefficients $\alpha(\tau)$ and $\beta(\tau)$ in (4) differs from those of the traditional quantile regression coefficients, $\gamma(\tau)$ in (2). In particular, they no longer describe the quantile function of the observed value of Y conditional on D, and X, a quantile function which confounds the influences of D and U in the presence of endogeneity. The coefficients $\alpha(\tau)$ can instead be interpreted as describing the hypothetical impact of an exogenous change in D on the quantiles of Y. This interpretation is formalized by defining the potential or latent outcome of Y for any given fixed value of d as

$$Y_d = d'\alpha(U) + X'\beta(U) \qquad U|X, Z \sim \text{Uniform(0,1)} \tag{7}$$

The coefficients in $\alpha(\tau)$ and $\beta(\tau)$ can then be seen as describing the conditional quantile function of the potential outcome Y_d conditional on X, which Chernozhukov and Hansen (2004b, 2005) define as the structural quantile function, $s_Y(\tau|d, x)$. They model it linearly as

$$s_Y(\tau|d, x) = d'\alpha(\tau) + x'\beta(\tau) \tag{8}$$

Because d is fixed, the conditional (on X) quantile function of the latent outcomes Y_d in (7) captures the effect of d on Y, uncontaminated by any feedback.

Since Y_d is latent, the structural quantile function $s_Y(\tau|d, x)$ cannot be estimated directly by quantile regression. However, under suitable regularity conditions, Chernozhukov and Hansen (2005) show that it may be identified by the conditional moment condition

$$P[Y \leq s_Y(\tau|D, X)|Z, X] = \tau \tag{9}$$

using the instrument Z. The instrumental quantile regression of Chernozhukov and Hansen (2004b), which we employ below, provides a clever method of estimating the structural quantile using the restriction in (9). Moreover, their results apply also to the case in which the original instrument Z is replaced by the fitted value from a standard first-stage linear regression of D on X and Z.

Although our study is the first to apply quantile regression methods to study the impact of Medicaid on savings behavior, quantile regression methods have recently been employed in a number of papers that consider the effect of government policy on savings incentives.

[9] Although this is referred to as a structural quantile model, we have not explicitly derived our specification from an economic model and therefore our use of this method may also be viewed as a quantile regression analog to reduced-form instrumental variable regression.

DOI: 10.1002/jae

Employing eligibility as an instrument for participation, Chernozhukov and Hansen (2004a) apply the instrumental quantile regression described above to analyze the impact of 401(K) retirement plans on savings. Using standard quantile regression, Chou *et al*. (2003) study the savings effect of the introduction of National Health Insurance in Taiwan in 1995. Given the absence of means tests, their study isolates the precautionary savings motive. Cagetti (2003) matches the parameters from a median regression to a wealth accumulation model with precautionary and retirement motives. He finds that households are impatient but risk averse and concludes that most savings are precautionary until age 45. Quantile regressions have also been employed in other contexts using data on wealth and savings, particularly to study wealth gaps, including those between racial groups (Hurst *et al*., 1998), across regions (Conley and Galenson, 1994, 1998), between natives and immigrants (Cobb-Clark and Hildebrand, 2006), and between cohorts (Kapteyn *et al*., 2005).

3. EMPIRICAL RESULTS

3.1. Summary Statistics of Household Characteristics across Net Worth Quantiles

We focus first on households with positive net worth, both because we are particularly interested in the savings effect of Medicaid, and also to facilitate comparison with the regression of Gruber and Yelowitz (1999). In order to provide summary statistics, we collect information from SIPP on household asset compositions. In Tables I and II, we then divide the households into 10 deciles ordered according to their total household net worth. For each household, we then calculate the average household characteristics within each decile. Table I focuses on household asset holdings and Medicaid eligibility, while Table II describes the other household characteristics, including age, race, marital status and education.[10]

Inspection of Table I reveals several interesting features. Row 1 shows average total net worth broken down by decile. The distribution of total net worth has a wide range and is highly skewed. The mean net worth is \$61,807, compared to a median of \$26,698. The average net worth in the bottom decile is just \$542, and, for the fifth decile, it is \$20,875, whereas the average for the top decile is \$295,114. In the next two rows, we divide net worth into total assets and total debt. Row 4 shows the percentage of households that have positive debt. One can see that this percentage is considerably lower among the bottom two deciles, 50% and 72% respectively, than it is for the middle and upper deciles, for which it is generally about 90%. This suggests that many of the poorer households may face credit constraints and have little capacity to borrow, most likely because few of these households have home equity or other collateral to borrow against.[11] Rows 5 and 6 further divide total debt into secured and unsecured debt. Secured debts include mortgages, car loans, and other debts taken against collateral, while unsecured debts consist primarily of credit card debt, store bills, and bank loans, which have no collateral attached and often require good credit ratings. In fact, the majority of debt is secured across all quantiles and may indicate a cap on unsecured borrowing ability.

Rows 7–8 show net equity in home (i.e., home value net of mortgage) and net equity in vehicle (i.e., car value net of car loans). Next, Rows 9–10 show the value of net worth excluding home

[10] The asset composition information, which we collect from SIPP, is not available in the Gruber and Yelowitz (1999) dataset that we use for the remaining tables.

[11] In results not reported in the table, the percentage of households having positive net equity in home is 0.03 and 0.11, respectively, for the bottom two deciles. This compares to 0.75 and 0.95 for the fifth and top decile, respectively.

DOI: 10.1002/jae

Table I. Summary statistics of household assets and debt across net worth deciles

Row	Variable	Net worth deciles										Full sample
		(0, 1) (poorest)	(1, 2)	(2, 3)	(3, 4)	(4, 5)	(5, 6)	(6, 7)	(7, 8)	(8, 9)	(9, 10) (richest)	
1	Net worth = total assets − total debt	542	2,251	5,408	11,337	20,875	33,926	51,739	76,952	119,963	295,114	61,807
2	Total assets	4,088	9,390	19,012	35,882	52,576	69,742	87,956	116,681	165,344	368,898	92,952
3	Total debt = secured debt + unsecured debt	3,546	7,138	13,603	24,544	31,700	35,816	36,216	39,729	45,381	73,784	31,145
4	Debt > 0	0.50	0.72	0.80	0.87	0.89	0.93	0.91	0.91	0.90	0.88	0.83
5	Secured debt	2,721	5,859	11,896	22,237	29,308	33,167	33,601	36,696	42,596	69,861	28,793
6	Unsecured debt	824	1,279	1,707	2,306	2,391	2,648	2,615	3,032	2,785	3,923	2,351
7	Net equity in home	129	420	1,529	5,265	12,216	22,117	34,180	49,517	70,958	105,023	30,134
8	Net equity in vehicle	914	2,257	3,635	4,404	4,627	4,996	5,622	6,662	7,843	10,001	5,096
9	Net worth excluding home	412	1,830	3,878	6,072	8,659	11,808	17,558	27,434	49,004	190,090	31,672
10	Net worth excluding home and vehicle	−501	−427	242	1,667	4,031	6,812	11,936	20,772	41,160	180,089	26,576
11	Medicaid eligible dollars	5,579	3,118	1,843	1,298	1,131	829	749	656	638	592	1,643
12	Medicaid eligible dollars/net worth	1029.34%	138.52%	34.08%	11.45%	5.42%	2.44%	1.45%	0.85%	0.53%	0.20%	2.66%
13	Standard deviation of Medicaid eligible dollars	9,698	7,184	5,067	3,968	3,596	2,831	2,779	2,506	2,274	2,069	5,029
14	Medicaid eligible dollars > 0	0.45	0.35	0.28	0.24	0.21	0.19	0.18	0.16	0.16	0.16	0.24
15	Currently covered by Medicaid	25.1%	10.9%	5.6%	4.8%	4.8%	3.4%	2.7%	1.6%	1.5%	0.9%	6.1%

Note: Figures are in 1987 dollars. The sample includes households with positive net worth in SIPP. Entries in columns 3–12 show the mean, proportion or standard deviation within a given net worth decile. Entries in the last column show the overall average, proportion or standard deviation using the full sample.

DOI: 10.1002/jae

Table II. Summary statistics of household characteristics across net worth deciles

	Net worth deciles										
	(0, 1) (poorest)	(1, 2)	(2, 3)	(3, 4)	(4, 5)	(5, 6)	(6, 7)	(7, 8)	(8, 9)	(9, 10) (richest)	Full sample
Head is female	0.45	0.38	0.32	0.27	0.23	0.23	0.22	0.19	0.17	0.16	0.26
Head age	36	35	35	37	39	41	43	45	47	49	40
Head black	0.19	0.15	0.11	0.09	0.09	0.07	0.06	0.04	0.03	0.01	0.08
Head white	0.77	0.82	0.85	0.87	0.89	0.91	0.92	0.94	0.95	0.95	0.88
Head high school diploma	0.39	0.42	0.39	0.38	0.36	0.38	0.37	0.36	0.30	0.26	0.36
Head some college	0.17	0.21	0.23	0.22	0.22	0.22	0.19	0.22	0.22	0.19	0.21
Head college diploma	0.09	0.14	0.20	0.23	0.24	0.24	0.28	0.29	0.36	0.47	0.25
Head married	0.39	0.49	0.55	0.63	0.68	0.71	0.73	0.77	0.80	0.81	0.66
Spouse high school diploma (if present)	0.43	0.46	0.47	0.44	0.46	0.46	0.45	0.46	0.40	0.35	0.44
Spouse some college	0.12	0.18	0.20	0.22	0.21	0.21	0.20	0.22	0.22	0.22	0.21
Spouse college diploma	0.05	0.09	0.13	0.17	0.18	0.18	0.21	0.22	0.26	0.35	0.20

Note: The sample includes households with positive net worth in SIPP. Entries in columns 2–11 show the mean or proportion within a given net worth decile. Entries in the last column show the overall average or proportion using the full sample.

and the value of net worth excluding both home and vehicle. This breakdown is important to our study for two reasons. First, both home equity and part of the value of the vehicle are excluded from the Medicaid asset tests. Therefore, the value of the household's net worth that is subject to an asset test lies between the value of net worth excluding equity in home and the value of net worth excluding equity in both home and car. Thus, this range gives a better indication of household net worth relative to the asset tests ceilings, which, when in place, were generally set in the \$1000–2000 range during this sample period. Secondly, excluding home and/or car equity may also give a better indication of a household's liquid assets, which may be more responsive to changes in Medicaid generosity. For the bottom decile, the average value of net worth excluding home equity is under \$500, while the average value of net worth excluding both home and car equity is negative. These averages increase for the higher deciles, but still remain below \$10,000 and \$5000 respectively up through the fifth decile. This suggests that a large portion of the population either qualifies or is relatively close to qualifying (i.e., within a few thousand dollars) for the asset test restrictions. In fact, the percentages with net worth excluding home and vehicle under \$1000, \$500, and zero are 44.36%, 40.25%, and 24.32%, respectively. Likewise, these figures also suggest relatively low liquid wealth among the lowest quantiles, and therefore perhaps little flexibility in adjusting consumption/savings decisions.

Rows 11–12 show both the dollar value of Medicaid eligible dollars and Medicaid eligible dollars as a percentage of total net worth. The average value of Medicaid eligible dollars for the bottom decile is \$5579 (1029.34% of net worth), as compared to \$1131 (5.42% of net worth) for the fifth decile, and only \$592 (0.20% of net worth) for the top decile. Not surprisingly, this suggests that Medicaid comprises a far more important factor in the decisions of households in the lower and middle deciles than in the top deciles. This might lead one to conjecture that the savings response to changes in Medicaid policy may differ substantially across wealth groups.

Rows 13–14 show both the standard deviation of Medicaid eligible dollars and the proportion of households that have a positive value for Medicaid eligible dollars. One can see that both

DOI: 10.1002/jae

values decrease monotonically with an increase in household net worth. The standard deviations of Medicaid eligible dollars are \$9698, \$3596, and \$2069, respectively, for the bottom, fifth, and top deciles. The percentage of households with positive Medicaid eligible dollars in the bottom, fifth, and top deciles are 0.45, 0.21, and 0.16, respectively. It is interesting to note that, even in the bottom decile, over 50% of households are not eligible for Medicaid and thus have no Medicaid eligible dollars. This appears to be primarily due to family and income composition restrictions.

The final row of Table I shows the actual Medicaid participation rates based on a SIPP survey question. Unlike the row above, which includes households that are eligible but not enrolled in Medicaid, as well as households with a positive probability of future eligibility, the rates shown in this row include only those households that are currently enrolled in Medicaid. Therefore, these actual enrollment rates are considerably lower than the potential eligibility rates shown in the row above. They also exhibit a sharp decline as wealth levels increase. Interestingly, even in the top three deciles, there are still some households enrolled in Medicaid (1.6%, 1.5%, and 0.9%, respectively). A casual examination suggests that these households tend either to have low or no labor income (despite their wealth), a large number of dependants, a family member receiving Supplementary Security Income, and/or a relatively old head of household.

Table II presents some basic household characteristics averaged across net worth deciles. These characteristics also differ considerably across quantiles. On average, the heads of households with lower net worth tend to be younger and have less education than those with high net worth. They are also more likely to be female, black, and unmarried. When married, their spouses tend to have less education. The difference in average characteristics across deciles also appears to become sharper at either end of the spectrum. The bottom and top two deciles stand out relative to the middle deciles, for which the characteristics tend to vary less across deciles. This suggests that behavior may be different across quantiles, particularly in the tails of the wealth distribution.

3.2. The Effect of Medicaid across Net Worth Quantiles

Gruber and Yelowitz (1999) estimate that a \$1000 increase in Medicaid eligible dollars reduces average household savings by 2.51%. To facilitate comparison with the quantile regression results discussed below, these estimates are replicated in column 2 of Table III. Their results support the contention that increased Medicaid generosity tends to reduce average savings due either to reductions in precautionary savings and/or the effect of asset testing. While these results provide convincing evidence on the average savings effects of Medicaid, they give little indication as to the distribution of this effect across wealth groups. As discussed earlier, this issue is important from the perspective of both a policy and economic standpoint. The considerable heterogeneity in both financial and household characteristics across different net worth quantiles, presented in the previous section, also suggests that the savings effect of Medicaid may vary across wealth quantiles.

Table III presents the analogous quantile regression results using the instrumental variable quantile regression method of Chernozhukov and Hansen (2004b, 2005).[12] The coefficients show

[12] Recall that the first stage consists of the same OLS regression as in Gruber and Yelowitz (1999), which has an excellent fit, with an F-statistic over 7000. The t-statistic on the instrument, SIMMED, is 74.65. In results available upon request, we compare the instrumental quantile estimates to those from the standard estimates. The coefficients on Medicaid eligible dollars are substantially and uniformly more negative when employing standard quantile regression than when employing instrumental quantile regression. This would be consistent with a reverse causality story in which increased wealth is

DOI: 10.1002/jae

Table III. The effect of Medicaid on savings across net worth quantiles

	2SLS	2-Stage IV quantile regressions Net worth quantiles								
	Mean	0.1 (poorest)	0.2	0.3	0.4	0.5 (median)	0.6	0.7	0.8	0.9 (richest)
Medicaid eligible dollars/1000	−0.0251	−0.0031	−0.0190	−0.0407	−0.0513	−0.0547	−0.0556	−0.0495	−0.0325	−0.0026
	(0.0054)	(0.0119)	(0.0097)	(0.0074)	(0.0062)	(0.0062)	(0.0060)	(0.0067)	(0.0091)	(0.0106)
Head is female	−0.3038	−0.5254	−0.4082	−0.3497	−0.2545	−0.2421	−0.1905	−0.1653	−0.1273	−0.1134
	(0.0294)	(0.0757)	(0.0521)	(0.0438)	(0.0361)	(0.0326)	(0.0298)	(0.0286)	(0.0294)	(0.0299)
Head age	0.0577	0.0117	0.0321	0.0631	0.0935	0.1141	0.1159	0.1148	0.0906	0.0377
	(0.0065)	(0.0150)	(0.0109)	(0.0092)	(0.0084)	(0.0077)	(0.0070)	(0.0068)	(0.0074)	(0.0078)
Head age^2/100	−0.0131	0.0311	0.0206	−0.0116	−0.0444	−0.0666	−0.0717	−0.0758	−0.0528	−0.0021
	(0.0075)	(0.0180)	(0.0127)	(0.0105)	(0.0094)	(0.0086)	(0.0078)	(0.0075)	(0.0082)	(0.0087)
Head black	−0.5629	−0.4237	−0.5726	−0.6285	−0.5968	−0.5259	−0.5223	−0.5284	−0.4998	−0.5743
	(0.0580)	(0.1295)	(0.1101)	(0.0811)	(0.0729)	(0.0729)	(0.0675)	(0.0649)	(0.0626)	(0.0678)
Head white	0.3492	0.5606	0.4916	0.3866	0.3850	0.3714	0.3076	0.2431	0.2202	0.1715
	(0.0514)	(0.1119)	(0.0975)	(0.0705)	(0.0615)	(0.0625)	(0.0586)	(0.0565)	(0.0550)	(0.0610)
Head high school diploma	0.5409	0.6990	0.7164	0.6553	0.5637	0.5181	0.4366	0.3771	0.3490	0.3322
	(0.0284)	(0.0678)	(0.0547)	(0.0434)	(0.0365)	(0.0314)	(0.0278)	(0.0265)	(0.0269)	(0.0290)
Head some college	0.7563	1.0418	1.0174	0.8701	0.7367	0.6491	0.5567	0.4964	0.4894	0.4826
	(0.0325)	(0.0758)	(0.0596)	(0.0475)	(0.0404)	(0.0350)	(0.0313)	(0.0306)	(0.0319)	(0.0350)
Head college diploma	1.1259	1.4638	1.4447	1.2483	1.0809	0.977	0.8619	0.8027	0.7754	0.7635
	(0.0334)	(0.0779)	(0.0600)	(0.0477)	(0.0410)	(0.0358)	(0.0324)	(0.0311)	(0.0317)	(0.0343)
Head married	0.3272	0.2793	0.4606	0.4357	0.4162	0.2914	0.1922	0.2006	0.1768	0.2838
	(0.0494)	(0.1146)	(0.0903)	(0.0806)	(0.0747)	(0.0682)	(0.0598)	(0.0558)	(0.0540)	(0.0546)
Spouse high school diploma	0.2167	0.4643	0.409	0.2917	0.2308	0.2326	0.2413	0.1510	0.1347	−0.0300
	(0.0476)	(0.1328)	(0.0874)	(0.0756)	(0.0712)	(0.0651)	(0.0563)	(0.0531)	(0.0534)	(0.0539)
Spouse some college	0.3825	0.7437	0.5510	0.4555	0.3296	0.3367	0.3775	0.2872	0.2689	0.0912
	(0.0530)	(0.1485)	(0.0969)	(0.0820)	(0.0751)	(0.0694)	(0.0600)	(0.0574)	(0.0583)	(0.0599)
Spouse college diploma	0.4121	0.7380	0.5269	0.4938	0.3743	0.3980	0.4770	0.4136	0.3822	0.2418
	(0.0552)	(0.1507)	(0.0929)	(0.0849)	(0.0776)	(0.0712)	(0.0609)	(0.0570)	(0.0583)	(0.0611)

Note: Also included, but not shown, are state and year fixed effects, state × year interactions, dummy variables for the number of family members, linear controls for age–gender groups and age–education groups, and a constant term. The second column shows the linear IV regression result. The remaining columns show the IV quantile regression results. Standard errors are in parentheses.

the effect of Medicaid on the conditional quantiles of net worth. We first consider the effect of Medicaid on the median household net worth shown in column 7. The results show that a \$1000 increase in Medicaid eligible dollars leads to 5.47% drop in median net worth, statistically significant at a 1% level. This confirms the robustness of the Gruber and Yelowitz (1999) result that Medicaid has a significantly negative effect on household savings. In fact, the median effect is stronger than the average effect.

We next investigate the effect of Medicaid spending on the remaining deciles. The estimated coefficients on Medicaid eligible dollars for the conditional quantiles of log net worth are given

associated with lower Medicaid eligibility, leading to a negative bias in quantile coefficients. This source of reverse causality is addressed by the instrumental quantile estimates via the use of an instrument in which Medicaid eligibility probabilities are not conditioned on wealth or income. The less strongly negative coefficients from the instrumental variable estimates would be consistent with the removal of this source of reverse causality and its resulting negative bias.

DOI: 10.1002/jae

together with their standard errors in the first two rows of Table III. These same estimates are also displayed in Figure 1, together with a 90% confidence interval. The estimates show a very clear pattern, as seen by the U-shape in Figure 1.[13] The estimate is quite small and insignificant for the bottom 0.1 quantile and just shy of significance for the 0.2 quantile with a two-sided p-value just above 5%. The estimates remain negative, but increase monotonically in magnitude and significance until reaching their trough at the 0.6 quantile. At this point, they then decrease monotonically in magnitude, remaining negative, but becoming insignificant again at the top 0.9 quantile.

The insignificant savings effect in the top decile may reflect both increased access to private insurance via employer benefit plans and a reduced attention paid to the details of Medicaid policy, given the lower likelihood of enrollment in a program primarily targeted towards poorer households. This result is also consistent with the model of Hubbard *et al*. (1995), in which wealthier households are less likely to respond to an increase in Medicaid generosity in the presence of an asset test.

Similar arguments can explain the fact that the coefficients decline in deciles 7–8. In fact, what seems most surprising about these results is that the decline is not more rapid. For example, the coefficient in decile 3 (−0.0407) is smaller in magnitude than the coefficient in decile 7 (−0.0495) and only moderately larger than the coefficient in decile 8 (−0.0325). It is not until the ninth decile that the Medicaid savings disincentive fully disappears.

As seen in row 15 of Table I, Medicaid enrollment rates in the seventh and eighth deciles are 2.7% and 1.6%, respectively. While this is less than half of the enrollment rate (5.6%) in the third decile, it may still be large enough for Medicaid to exert some influence on the decision making

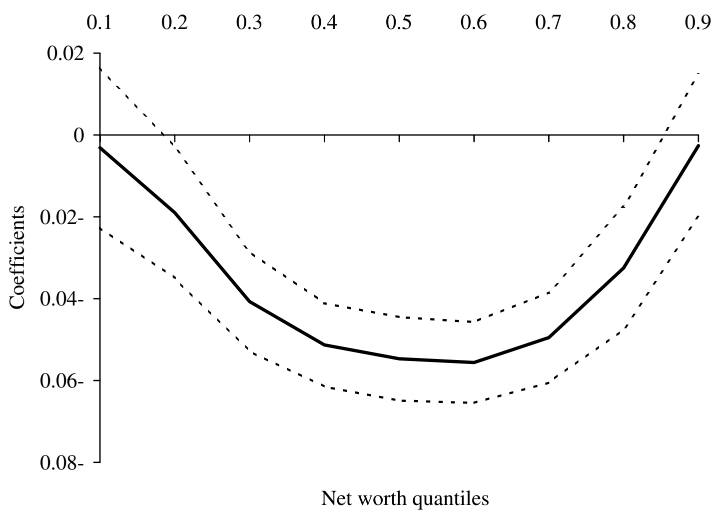

Figure 1. Summary of the effect of Medicaid on savings across net worth quantiles. The solid line summarizes the estimated coefficients of Medicaid eligible dollars/1000 in Table III. The dotted line plots the 90% confidence interval for the estimated coefficients

[13] Due to the large number of dummy variables in the regression we encountered some near singularities in the matrix inversions. We also reran these quantile results without including the state–year interactions dummies, obtaining a similar U-shape.

DOI: 10.1002/jae

of households in these deciles. Moreover, the potential availability of Medicaid in future bad states, such as unemployment spells, may influence savings behavior in households not currently enrolled or eligible for Medicaid. As seen in row 14 of Table I, the percentage of households with a positive probability of future Medicaid eligibility is considerably higher than the current enrollment: 0.18 and 0.16 in deciles 7 and 8, respectively. To the extent that moderately wealthy households view inter-vivos transfers as a potential mechanism for circumventing future Medicaid eligibility requirements, this may further enhance the role of Medicaid policy in their savings decisions. Finally, if health is a normal good then wealthier households would demand more health services[14] and might therefore keep a larger buffer stock available as precautionary savings in the absence of Medicaid. Thus, it is not inconceivable that Medicaid would impact the savings decisions of these households.

The question is then whether the magnitudes of the savings responses for these relatively wealthy households appear reasonable. The regression coefficients estimate the percentage change in savings due to a one-dollar increase in Medicaid. Because net worth is by definition higher for wealthier households, these percentage changes translate into fairly large dollar changes in deciles 7–8. In fact, as seen in panel A of Table IV, when measured in dollar changes the Medicaid savings disincentives are largest for the eighth quantile, implying a \$3199.9 drop in savings in response to a \$1000 increase in Medicaid eligible dollars. This is far larger than the dollar response for the third decile, for which the same \$1000 increase in Medicaid eligible dollars leads to only a \$340.7 reduction in savings. To the extent that the estimated savings response in the upper middle quantiles are viewed as implausibly large, it could suggest that something other than a causal savings disincentive effect is behind the negative correlation between Medicaid generosity and savings, at least for these wealthier households.

Table IV. The effect of Medicaid on savings across net worth quantiles: magnitude and elasticity

	Net worth quantiles								
	0.1 (poorest)	0.2	0.3	0.4	0.5 (median)	0.6	0.7	0.8	0.9 (richest)
Panel A: Dollar change in savings in response to a \$1000 increase in Medicaid eligible dollars (coefficient × corresponding quantile average net worth)									
Medicaid eligible dollars/1000	−4.3	−73.7	−340.7	−826.2	−1498.8	−2381.5	−3185.1	−3199.9	−539.6
Panel B: Percentage change in savings in response to the percentage change of Medicaid eligible dollars (elasticity = coefficient × corresponding quantile average of Medicaid eligible dollars)									
Medicaid eligible dollars/1000	−0.013	−0.047	−0.064	−0.062	−0.054	−0.044	−0.035	−0.021	−0.002

Note: For each quantile, j, the magnitudes and elasticities in the table entries are evaluated at the values of net worth and Medicaid eligible dollars, averaged across only SIPP households within one decile of j (i.e., averaged across $[j-0.1, j+0.1]$). For net worth, these averages can be calculated using the information in row 1 of Table I. For example, the average net worth for quantile 0.3 is equal to 1/2(\$5408 + \$11, 337) = \$8372.5. For Medicaid eligible dollars, they may be calculated using the information in row 11 of Table I. For example, the average Medicaid eligible dollars for quantile 0.3 is equal to 1/2(\$1843 + \$1298) = \$1570.5.

[14] We thank Michael Hoy for pointing this out.

DOI: 10.1002/jae

On the other hand, this comparison corresponds to a policy experiment in which the expected value of Medicaid is expanded as much for wealthy households as for poor households. However, recall that the expected value of Medicaid (MED) equals the probability of eligibility times the value of benefits to eligible households. Given that the eligibility probabilities are much lower for wealthier households, such a policy would require a greater increase in the dollar value of benefits to eligible wealthy households than to eligible poor households. An alternative policy experiment would be one in which the value of Medicaid is expanded proportionally for each quantile rather than by an equal fixed dollar amount for the whole population. This experiment could have very different implications because a $1000 increase in the expected value of Medicaid corresponds to a 133.5% increase in the average expected value for households in decile 7, but only a 54.3% increase in decile 3. Therefore, we next examine the percentage change in savings in response to a one-percentage change in the average value of Medicaid eligible dollars in each quantile. Panel B of Table IV displays these elasticities, which show a similar U-shape as the coefficient estimates. However, the elasticities for deciles 7–8 are considerably lower than those for deciles 3–4.[15]

Most interesting is the effect of Medicaid on the lower net worth quantiles to whom Medicaid is generally targeted. For these households, the value of Medicaid is quite large relative to net worth. Thus, one might have expected a more pronounced savings response to Medicaid in the bottom quantiles, whereas they in fact respond much less. As shown in Table III, the coefficients on Medicaid eligible dollars for the bottom two deciles are −0.0031 (insignificant) and −0.0190 (nearly significant), respectively. The effect becomes strongly significant and increases in magnitude to −0.0407 and −0.0513, respectively, for the third and fourth deciles.

Although this result may seem surprising given the importance of Medicaid to poorer households, two plausible explanations nevertheless present themselves. The first is that households in the lower quantile have little to no precautionary savings to draw down in response to an expansion in Medicaid eligibility. Average net worth excluding home and car equity, shown in Table I, are already negative for the bottom two deciles. Likewise, given their credit constraints, these households may also have little capacity to borrow further. Presumably, in the absence of wealth and borrowing constraints, they would respond to the reduction of future medical expenditure uncertainties associated with increased Medicaid generosity by reducing their savings or increasing their borrowing. However, this precautionary saving channel may be blocked on account of low wealth levels and borrowing constraints. As we explore below, a second possible explanation is that the asset-testing channel may also become less important in the marginal savings decisions of the poorest households.

3.3. Asset Testing across Quantiles

By including the interaction between Medicaid eligible dollars and asset testing in their regression,[16] Gruber and Yelowitz (1999) find that the average savings disincentive effect of Medicaid

[15] Because the regressor, MED, enters in levels, the formula for the elasticity is given by $\alpha(\tau)$ MED, where $\alpha(\tau)$ is the quantile coefficient on MED and thus depends on the value of MED at which it is evaluated. For the regression it is common to evaluate this at the sample average, but since average values of MED differ substantially across low and high net worth quantiles this would likely be misleading for quantiles other than the median. Instead, for each quantile, say τ, we estimate the average value of MED across only those households whose net worth is within one decile of τ (i.e., within $\tau \pm 0.1$).

[16] Note that the state, year, and state–year interaction dummy variables, which absorb the asset test dummy variable, control for the independent effect of the asset test on net worth.

DOI: 10.1002/jae

is doubled in the presence of an asset test. (Their regression results are reproduced in the second column of Table V.) In particular, households appear to substantially spend down their wealth to gain Medicaid eligibility in the presence of an asset test, once other binding Medicaid eligibility requirements, such as income tests or demographic restrictions, are removed. This confirmed one of the main predictions of Hubbard *et al*. (1995). A second important prediction of Hubbard *et al*. (1995), so far unaddressed, is that the effect of the asset test should differ substantially across households of different means. In this section, we investigate the differential impact of Medicaid asset tests across net worth quantiles through the inclusion of the asset test interaction in the instrumental quantile regression.

While the average impact of Medicaid is found to be particularly strong in the presence of an asset test, this tells us little about the variation of this effect across quantiles. One might conjecture that the extent to which a household's saving decision is affected by the asset test should depend, in part, on the level of its net worth relative to the asset test ceiling. In particular, it may depend on whether the household's wealth is below or above the asset ceiling and, if above, then by how much. The stylized model in Hubbard *et al*. (1995) implies that households with initial wealth not too far above asset testing ceilings will react strongly to the asset test, whereas very wealthy households should not react at all, since they are willing to forgo Medicaid benefits in order to avoid the asset test. In addition, we have argued above that households whose initial wealth lies below the asset test ceiling may also be less affected by asset test interactions, since they require no further asset reductions in order to qualify for Medicaid.

The bottom row of Table V shows the interactive effect of the asset-testing dummy variable and Medicaid eligible dollars across net worth quantiles. Like the coefficients on Medicaid eligibility dollars discussed above, the coefficients on the interaction term are also small and insignificant for the top and bottom decile. However, they are significantly negative for the remaining quantiles and are largest for quantiles 0.2 to 0.5. This confirms the conjecture above that households in the lower–middle quantiles respond most strongly to asset tests, while those in the bottom quantile have no need to adjust wealth levels in response to asset tests and those in the top quantiles choose not to.

Table V. Asset testing interaction across net worth quantiles

	2SLS	2-stage IV quantile regressions Net worth quantiles								
	Mean	0.1 (poorest)	0.2	0.3	0.4	0.5 (median)	0.6	0.7	0.8	0.9 (richest)
Medicaid eligible dollars/1000	−0.0181 (0.0057)	−0.0008 (0.0114)	−0.0132 (0.0084)	−0.0339 (0.0073)	−0.0444 (0.0065)	−0.0502 (0.0059)	−0.0505 (0.0062)	−0.0463 (0.0065)	−0.0283 (0.0094)	−0.0025 (0.0099)
Kept asset test × Medicaid eligible dollars/1000	−0.0256 (0.0055)	−0.0143 (0.0121)	−0.0262 (0.0101)	−0.0227 (0.0076)	−0.0257 (0.0073)	−0.0227 (0.0065)	−0.0215 (0.0061)	−0.0181 (0.0059)	−0.0131 (0.0070)	−0.0067 (0.0076)

Note: Additional regressors include the set of covariates listed in Table III and the note to that table. The second column shows the linear IV regression result. The remaining columns show the IV quantile regression results. Standard errors are in parentheses.

The table also shows the coefficients on Medicaid eligible dollars after controlling for the interaction between Medicaid eligible dollars and the asset test (top row). These coefficients may now be interpreted as showing the influence of Medicaid eligible dollars on the quantiles of net worth in the absence of the asset test. In other words, they are likely to capture the pure wealth or precautionary savings effects. It is interesting to compare these estimates to the equivalent coefficients on Medicaid eligible dollars in Table III (top row), in which we do not control for the interaction with asset testing. This comparison is presented in Figure 2. The height of the dark bars on the left shows the coefficients on Medicaid eligible dollars from Table III, where we do not control for asset testing. The gray bars in the middle show the coefficients on Medicaid eligible dollars from Table V after controlling for the asset-testing interaction. Finally, the white bars on the right show the value of the coefficient on the interaction term described above.

Inspection of Figure 2 reveals that, after controlling for the asset test interactions in Table V, the coefficients on Medicaid eligible dollars are uniformly reduced across quantiles relative to the original estimates in Table III. This confirms that asset testing interactions can explain part of the net worth reductions associated with Medicaid. This appears to be true across all net worth deciles.

Therefore, it is clear that asset testing plays an important role in the savings decision. On the other hand, although the coefficients on Medicaid eligible dollars in Table V are somewhat smaller in magnitude than those shown in Table III, they nonetheless remain significant for all but the top decile and the bottom two deciles. In fact, for most of the middle deciles, they remain highly significant. Thus, as expected, asset testing explains part, but not all, of the negative effect of Medicaid on net worth.

Likewise, after controlling for asset testing interactions, the coefficients on Medicaid eligible dollars in Table V, shown by the middle bars of Figure 2, show only a somewhat attenuated

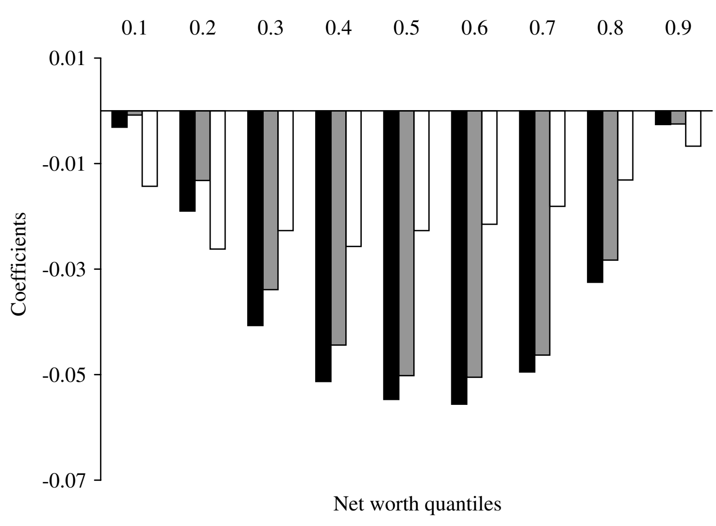

Figure 2. Summary of the results in Tables III and V. The left (dark), middle (gray) and right (white) columns represent the estimated coefficients on Medicaid eligible dollars/1000 in Table III, Medicaid eligible dollars/1000 in Table V and Kept asset testing $\times$ Medicaid eligible dollars/1000 in Table V, respectively.

DOI: 10.1002/jae

version of the original U-shape found in the coefficients in Table III (the left bars in Figure 2). Even after accounting for asset testing, we still find a much stronger effect of Medicaid eligible dollars on the middle quantiles than we do on the top and bottom ends of the distribution. In other words, asset testing is again just part of the story. Differential responses to asset testing explain only some of the differences across quantiles. The remaining differences must be explained by other channels. As discussed above, for the top decile this may simply reflect the fact that Medicaid plays a much smaller relative role in household finances. For the bottom quantiles, we have argued above that low existing precautionary savings and constraints on borrowing may limit the normal precautionary savings effect.

3.4. Results Including Households with Negative Net Worth

In the results presented above, we excluded households with non-positive net worth. This allowed us to employ a log transformation of net worth, thereby providing a convenient interpretation of the coefficients in terms of percentage changes. It also allowed for a clean comparison to the earlier results of Gruber and Yelowitz (1999), whose regression results are estimated using households with positive net worth. Nevertheless, in order both to ensure robustness to potential sample selection concerns[17] and also to estimate the effects of Medicaid on the very poorest households, it is necessary to include households with zero or negative net worth. As these households are relatively likely to qualify for Medicaid and also have the least savings, it may be of interest to consider this sub-population when analyzing the effect of Medicaid on savings.

We now expand our sample to include the households with zero or negative net worth in addition to the positive net-worth households employed above. This yields a total of 52,706 households, of which 7043 (or 13.36%) report zero net worth and 5221 (or 9.91%) report negative net worth.

Because the log transformation is defined only for positive values, we may no longer employ log net worth as our dependent variable. This issue arises often when working with wealth data. As a solution to this problem, Burbidge *et al.* (1988) and Pence (2006) suggest transforming net worth by the inverse hyperbolic sine transformation

$$g(y_t, \theta) = \log(\theta y_t + (\theta^2 y_t^2 + 1)^{1/2})/\theta = \sinh^{-1}(\theta y_t) \tag{10}$$

which admits non-positive values of y_t, in place of the more standard log transformation. This transformation of net worth has been employed in recent work by Cobb-Clark and Hildebrand (2006) using a value of $\theta = 1$, in which case it simplifies to

$$g(y_t, 1) = \log(y_t + (y_t^2 + 1)^{1/2}) = \sinh^{-1}(y_t) \tag{11}$$

In the results discussed below, we also employ the specialized version of the inverse hyperbolic sine transformation given in (11).[18]

[17] Gruber and Yelowitz (1999) also provide probit results on the probability of a household's having positive net worth and use these results to convincingly argue that sample selection bias could not be large enough to undo their main results.
[18] The transformation in (10) is linear near the origin but approximates a vertically shifted log-function for large positive y_t values. The parameter θ governs both the speed of this transition and the size of the shift. Using $\theta = 1$ we closely approximate (by less than a \$1.0 difference) our previous log specification for positive net worth values as small as \$100. By contrast, employing a value of θ near zero approximates the regression in levels for all but very large values of $|y|$.

DOI: 10.1002/jae

Table VI shows the instrumental quantile regression results including households with positive, negative, and zero net worth. The dependent variable in both panels is the inverse hyperbolic sine transformation of net worth. Panel A, which shows quantile coefficients describing the effect of Medicaid on net-worth, employs the same regressor, instrument, and control variates as Table III. Likewise, panel B, which includes also the asset test dummy variable, includes the same regressors, instruments, and control variates as in Table V.

With the exception of the first two deciles, for which net worth (y) is zero, simple calculations show that the coefficient estimates in panel A of Table VI closely approximate the quantity $\frac{\partial y/\partial_{\mathrm{MED}}}{|y|}$ that corresponds to the interpretation of the coefficient on MED in the previous log-level specification employed in Table III.[19] This is expected since the transformation in (11) closely resembles the log transformation for all but the poorest positive net worth households (see footnote 18). Thus, the coefficients in Table VI using the inverse hyperbolic transform have (approximately) the same interpretation as those using the log specification in Table III.

On the other hand, due to the inclusion of non-positive net worth households, the τ quantile in Table VI corresponds to a lower value of net worth than the same τ quantile in Table III. Therefore, one cannot meaningfully compare the magnitudes of the coefficients across these tables. Nevertheless we may still compare the overall shape and pattern of the quantile coefficients. In panel A, we again observe a U-shaped pattern to the quantile coefficients. This confirms our earlier finding that the savings effect of Medicaid is strongest in the middle net worth quantiles. However, because we no longer truncate the non-positive net worth households, this U-shape is shifted somewhat to the right. For example, using this full sample, the bottom two quantile coefficients are insignificant, whereas in Table III only the bottom coefficient turned up insignificant. Thus, we find no discernible effect of Medicaid on the savings on the bottom 20% of households, when including households with non-positive net worth.

The quantile coefficients in Table VI, panel B, also show a pattern similar to those in Table V. The top row shows the effect on the quantiles of net worth in the absence of an asset test, while the third row shows the quantile coefficients on the asset-test/Medicaid interaction term. Standard errors are given in parentheses below the estimates. The negative savings effect of the Medicaid/asset test interaction term is again strongest for the lower–middle net worth quantiles. As before, this effect dissipates in the top quantiles and it now disappears altogether for the bottom two deciles. In fact, somewhat surprisingly, these two coefficients have a positive sign.

To investigate the robustness of our choice, in results available upon request, we have also rerun our results using values of θ ranging between 0.1 and 10, obtaining similar overall U-shaped patterns. Burbidge *et al.* (1988) and Pence (2006) develop methods for selecting θ in mean and median regression, respectively, but we are not aware of existing selection methods for general quantile or IV regression.

[19] In fact, these approximations are accurate out to at least seven digits. The corresponding comparisons for the coefficients in panel B apply up to a similar margin of approximation error. For large $|y|$, this close approximation can be understood by the relation $\frac{\partial y/\partial_{\mathrm{MED}}}{|y|} = \alpha(\tau)(1/|y|)\left(\frac{1}{\partial g(y,1)/\partial y}\right) \approx \alpha(\tau)$, where $\partial g(y,1)/\partial y = \frac{(y^2+1)^{1/2}+y}{y(y^2+1)^{1/2}+(y^2+1)}$. For deciles 1 and 2 $y = 0$, so that $\frac{\partial y/\partial_{\mathrm{MED}}}{|y|}$ is not well defined.

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Table VI. Results including households with non-positive net worth quantiles

	2SLS	2-stage IV quantile regressions Net-worth quantiles								
	Panel A: The effect of Medicaid on savings across net worth quantiles									
	Mean	0.1 (poorest)	0.2	0.3	0.4	0.5 (median)	0.6	0.7	0.8	0.9 (richest)
Medicaid eligible dollars/1000	−0.0537 (0.0135)	−0.0068 (0.0606)	0.0013 (0.0245)	−0.0690 (0.0132)	−0.0900 (0.0109)	−0.1161 (0.0081)	−0.1274 (0.0077)	−0.1056 (0.0097)	−0.0786 (0.0082)	−0.0533 (0.0083)
	Panel B: Asset testing interaction across net worth quantiles									
	Mean	0.1 (poorest)	0.2	0.3	0.4	0.5 (median)	0.6	0.7	0.8	0.9 (richest)
Medicaid eligible dollars/1000	−0.0506 (0.0141)	−0.0323 (0.0558)	−0.0176 (0.0279)	−0.0662 (0.0135)	−0.0798 (0.0108)	−0.1069 (0.0087)	−0.1156 (0.0090)	−0.0932 (0.0108)	−0.0704 (0.0079)	−0.0511 (0.0086)
Kept asset test × Medicaid eligible dollars/1000	−0.0145 (0.0128)	0.1256 (0.0379)	0.0434 (0.0225)	−0.0292 (0.0129)	−0.0537 (0.0095)	−0.0455 (0.0079)	−0.0381 (0.0076)	−0.0372 (0.0073)	−0.0273 (0.0062)	−0.0183 (0.0059)

Note: The sample includes all (52,706) households with positive, zero and negative net worth in SIPP. The dependent variable is the hyperbolic sign transformation of net worth. Additional regressors include the set of covariates listed in Table III and the note to that table. The second column shows the linear IV regression results. The remaining columns show the IV quantile regression results. Standard errors are in parentheses.

3.5. The Interaction between Labor Income, Medicaid, and Asset Testing

Incorporating information on labor income provides two important robustness checks. First, following Gruber and Yelowitz (1999), our baseline specification excluded labor income under the assumption that labor income is orthogonal to the instrument (SIMMED). However, it is possible that this assumption could be violated in practice. For example, it would be unlikely to hold if income varies across household sizes. Labor income can also be used to assess the sensitivity of our qualitative conclusions to the implicit use of net worth as the indicator of affluence. In the work presented above, we examined the effect of Medicaid on savings across households with different wealth levels. However, net worth is just one measure of a family's affluence (or poverty). Some families may have high income, but low or negative net worth. An example would be a head of household who recently graduated from college with a good job but large student loans. Therefore, we also consider the robustness of our findings when affluence/poverty is defined in terms of labor income instead of wealth holdings. In other words, we consider the savings disincentive effects of Medicaid as a function of household income rather than household wealth. In order to mitigate endogeneity between net worth and income, we focus exclusively on labor income.

In column 1 of Table VII, we re-estimate the mean results for households with positive net worth shown in column 1 of Table III with the log of family labor income added as an additional control variate. The results confirm that labor income is important in explaining net worth, but its inclusion does not much change the regression coefficient on Medicaid eligible dollars.[20] In column 2, we estimate the mean effect for the households with positive and non-positive net worth, again controlling for labor income. For this population, the mean effect becomes insignificant, suggesting that the mean effect differs depending on the population under consideration. This is consistent with our earlier finding that savings disincentives are weaker and insignificant for poorer households, many of whom are excluded from the regression including only households with positive net worth.

In order to explore these results further and also to assess the robustness of our findings when affluence is redefined in terms of income rather than wealth, we next consider the savings effect of Medicaid as a function of labor income. Since net worth is the dependent variable, the quantile regression is the appropriate approach when considering the savings effect of Medicaid as a function of net worth. However, the quantile regression is no longer appropriate when considering the savings effect of Medicaid as a function of labor income, since labor income is not the dependent variable and must instead be treated as a regressor. Therefore, in column 3 of Table VII, we instead interact Medicaid with dummy variables corresponding to the five quintile ranges ranges of labor income.[21] The last four of these dummy variables are denoted by Labor income quintile j, $j = 2, 3 \ldots 5$ and shown in the bottom four rows of column 1.[22] The five interaction terms, denoted by Medicaid eligible dollars/1,000 × Labor income quintile j, $j = 1, 2, \ldots, 5$, are shown in rows 3–7 of Table VII. We instrument the Medicaid interaction term variables in rows 3–7 using the interaction of the labor quintile dummy variables with SIMMED, the instrument employed previously for Medicaid eligible dollars. We employ the same sample, dependent variable

[20] In results available upon request, we also found IV quantile results similar to those in Table III when controlling for labor income.
[21] Because approximately the bottom 20% of households in our sample have no labor income, we break labor income into quintiles rather than deciles.
[22] Both the first labor income dummy variable and Medicaid eligible dollars themselves are excluded in order to avoid the dummy variable trap.

DOI: 10.1002/jae

Table VII. Labor income, Medicaid and asset test

	(1)	(2)	(3)
Medicaid eligible dollars/1000	−0.0234	−0.0170	
	(0.0054)	(0.0136)	
Ln(Labor income)	0.0516	0.4368	
	(0.0034)	(0.0099)	
Medicaid eligible dollars/1000 × Labor income quintile 1			0.0025
			(0.0145)
Medicaid eligible dollars/1000 × Labor income quintile 2			−0.0557
			(0.0164)
Medicaid eligible dollars/1000 × Labor income quintile 3			−0.0451
			(0.0187)
Medicaid eligible dollars/1000 × Labor income quintile 4			0.0161
			(0.0211)
Medicaid eligible dollars/1000 × Labor income quintile 5			0.0399
			(0.0254)
Labor income quintile 2			3.0318
			(0.1182)
Labor income quintile 3			3.9166
			(0.1240)
Labor income quintile 4			5.1587
			(0.1267)
Labor income quintile 5			6.2963
			(0.1258)

Note: Column 1 includes all households with positive net worth in SIPP. Columns 2 and 3 include all households with positive, zero and negative net worth in SIPP. Additional regressors include the set of covariates listed in Table III and the note to that table. Standard errors are in parentheses.

transformation, and control variates as in Section 3.4 above. This provides a simple convenient mechanism by which we allow the effect of Medicaid eligible dollars on savings to vary across the quintiles of labor income.

The results for this regression are shown in column 3 of Table VII. These results confirm the robustness of our previous findings. The estimates in the third row show the impact of Medicaid eligible dollars on savings for the poorest 20% of households as measured by labor income. Among these households, we find no evidence that increased Medicaid eligibility leads to a decline in savings. In fact, the coefficient is positive but insignificant. Thus, no matter whether we define poverty in terms of asset-poor or income-poor, we find no impact of Medicaid on the savings of the very poorest households. The coefficients on the remaining four interaction terms (in rows 2–5) also demonstrate a U-shaped pattern, qualitatively similar to that found earlier in Figure 1. We also control for the direct effect of labor income using the four dummy variables shown in the bottom rows of the table. Not surprisingly, their coefficients increase monotonically. This confirms that, after controlling for labor income, Medicaid still has an impact on the savings of the lower–middle-income households, but has no significant impact on the savings of either low-or high-income households.

4. DISCUSSION AND SUMMARY

In this paper, we study the differential impact of Medicaid eligibility and generosity across different net worth households. We show that the disincentives associated with Medicaid generosity vary

DOI: 10.1002/jae

considerably across household net worth quantiles. In fact, we uncover a clear U-shaped pattern across the quantile coefficients, with the disincentive effect peaking near the middle of the net worth distribution, but becoming small and insignificant at both its top and bottom end.

Our results have several important implications. In particular, there is no evidence that Medicaid expansions crowd out the savings of the very poorest households, whereas crowd-out may be substantial for moderately poor households. Surprisingly, the crowd-out is also large for moderately wealthy households (deciles 7–8), especially when responses are measured in dollar magnitudes. The crowd-out effect is generally heightened in the presence of an asset test, particularly for the lower–middle quantiles of the asset and income distributions. Yet, even with an asset test in place, there is still no evidence of savings crowd-out for the bottom quantiles.

This has interesting economic implications. We find that Medicaid generosity has little savings effect for the wealthiest households (decile 9), but quite a strong effect on households in the middle quantiles. Moreover, in the presence of an asset test, the effect appears to be strongest for those households whose asset levels are not much above the asset test ceiling. This is generally supportive of the central theoretical mechanism at work in Hubbard *et al*. (1995), in which the utility cost of the savings adjustment required to meet the asset test is moderate for poor households but becomes prohibitive for wealthier households.

On the other hand, we find no evidence of Medicaid induced savings disincentives for households in the bottom quantiles of either the income or wealth distributions. This is also consistent with the findings of Hurst and Ziliak (2006), who find no evidence of asset-test based savings disincentives for female-headed households with children, a demographic whose wealth and earnings are concentrated in the lower quantiles. Several potential explanations for the lack of savings response by poor households present themselves. First, since many of these households have virtually no precautionary savings to spend down and little room to borrow on account of their low income, they may not be able to further reduce their precautionary savings in response to a Medicaid expansion. Likewise, these same households have too few assets to be affected by the asset test limits. Secondly, the poorest households are likely to be eligible for other public insurance programs and may therefore be less responsive to changes in Medicaid coverage. For example, a household might not increase its savings in response to the removal of the Medicaid asset test if they still need to satisfy asset tests to qualify for other government programs.[23] This suggests that it may be important to study the combined impact of public insurance programs on poor households. It may also be possible that some of these households are myopic (Feldstein, 1987), and thus do not respond to Medicaid incentives. Alternatively, given low incomes, they may envision little prospect of accumulating precautionary savings substantial enough to be useful in the event of large discrete medical costs. More work may be required to fully understand their lack of savings.

Finally, we acknowledge some caveats associated with this reduced form approach.[24] From the perspective of a life cycle model, what we attempt to capture is essentially the impact of solving the model with and without Medicaid policy, holding all other aspects constant. Despite the carefully developed instrument and the many control variates included in the empirical specifications, there are still some reasons to suspect that the estimates from our reduced-form approach may differ in certain respects from the structural effects that are of ultimate interest.

[23] Similarly, French and Jones (2004, see section 4.3 of their extended version) find an inverted U-shape to the value that households would be willing to pay for health insurance. They attribute this to the fact that the poorest households are already protected by an implicit consumption floor.

[24] We thank the co-editor, John Rust, for several very thoughtful comments on these issues.

DOI: 10.1002/jae

First, the identification strategy treats policy changes as if they were exogenous experiments rather than outcomes of a policy process, which, while exogenous to individual level household net worth, may respond to larger trends in wealth or other household characteristics. For example, increases in average wealth may help accommodate more generous public insurance via an expanded tax base. Likewise, trends in household composition, such as the proportion of single-headed households, may alter the political constituencies that support Medicaid. As discussed in Section 2.2, to some extent this endogeneity may be partially (but only partially) mitigated, via the inclusion of year–state interaction dummy variables that partial out the policy induced variation between state–year cells. The identification relies rather on the within state–year variation in household responses to these policy changes that arise due to differences in the quasi-exogenous household characteristics, such as family member ages, used in the instrumental variable.

A second potential concern is that we do not control for the value of other public insurance programs, such as Supplementary Security Income (SSI) and Aid to Families with Dependent Children (AFDC). This may bias the results in either direction by confounding changes in the generosity of other social insurance programs with those of Medicaid. In addition, complicated interactions between the asset tests of various programs could exist. For example, households enrolled in multiple programs may not increase their savings until all relevant asset tests are lifted. This issue could, in principle, be partially addressed in a reduced-form context by developing household present expected value measures, similar to the Medicaid eligible dollars measure of Currie and Gruber (1996a,b), for programs such as SSI and AFDC. While this may be an interesting line of future research, without the aid of a structural model, it is not clear whether the simple inclusion of these measures as control variates would be sufficient to capture the complex interactions between government programs.

Certain higher-level general equilibrium effects that might be expected from large changes in Medicaid policy may also be missed by our analysis. For example, in the absence of Medicaid, there might be greater incentives for low-wage employers to provide medical insurance, or insurers might tailor new private health insurance plans to low-income households. Likewise, the composition of the health care industry and thus health costs might also be affected by the removal of a large government purchaser.

In future research, it might be interesting to further distinguish between the different channels by which Medicaid impacts savings. For example, public insurance programs, particularly when coupled with a means test, may also lead to reductions in labor income, which may in turn reduce savings. The savings disincentives which we estimate combine this indirect channel with the direct impact of Medicaid, whereas it might be useful in future work to disentangle the two. It would also be interesting to distinguish between true reductions in savings and inter-vivos transfers.

ACKNOWLEDGEMENTS

We are grateful to Jonathan Gruber and Aaron Yelowitz for generously providing us with their data. We also thank Victor Chernozhukov and Christian Hansen for use of their instrumental quantile regression code. This paper has benefited substantially from comments by John Rust and two anonymous referees. We also thank Varouj Aivazian, Michael Baker, Stacey Chen, Chuan Goh, Vincent Hildebrand, Kim Huynh, Michael Hoy, John Bailey Jones, Lonnie Magee, Robert McMillan, Christine Neill, Karen Pence, Eduardo Pontual Ribeiro, Jeff Racine, Aloysius Siow (discussant), Michael Smart, seminar participants at SUNY Albany and McMaster, and

DOI: 10.1002/jae

conference participants at the 2005 Canadian Economic Association Meetings and the 2006 Midwest Econometrics Group Meeting, for useful comments. The authors acknowledge financial support from the Social Science and Humanities Research Council of Canada under grant numbers 410-2001-1527 (Maynard) and 410-2005-0206 (Qiu). We take full responsibility for any remaining errors.

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DOI: 10.1002/jae