The Value of Medicaid: Interpreting Results from the Oregon Health Insurance Experiment

Amy Finkelstein, Nathaniel Hendren, and Erzo F.P. Luttmer*

June 2018

Abstract

We develop a set of frameworks for welfare analysis of Medicaid and apply them to the Oregon Health Insurance Experiment, a Medicaid expansion for low-income, uninsured adults that occurred via random assignment. Across different approaches, we estimate recipient willingness to pay for Medicaid between \$0.5 and \$1.2 per dollar of the resource cost of providing Medicaid; estimates of the expected transfer Medicaid provides to recipients are relatively stable across approaches, but estimates of its additional value from risk protection are more variable. We also estimate that the resource cost of providing Medicaid to an additional recipient is only 40% of Medicaid's total cost; 60% of Medicaid spending is a transfer to providers of uncompensated care for the low-income uninsured.

1 Introduction

Medicaid is the largest means-tested program in the United States. In 2015, public expenditures on Medicaid were over \$550 billion, compared to about \$70 billion for food stamps (SNAP), \$70 billion for the Earned Income Tax Credit (EITC), \$60 billion for Supplemental Security Income

*MIT, Harvard, and Dartmouth. We are grateful to Lizi Chen for outstanding research assistance and to Isaiah Andrews, David Cutler, Liran Einav, Matthew Gentzkow, Jonathan Gruber, Conrad Miller, Jesse Shapiro, Matthew Notowidigdo, Ivan Werning, three anonymous referees, Michael Greenstone (the editor), and seminar participants at Brown, Chicago Booth, Cornell, Harvard Medical School, Michigan State, Pompeu Fabra, Simon Fraser University, Stanford, UCLA, UCSD, the University of Houston, and the University of Minnesota for helpful comments. We gratefully acknowledge financial support from the National Institute of Aging under grants RC2AGO36631 and R01AG0345151 (Finkelstein) and the NBER Health and Aging Fellowship, under the National Institute of Aging Grant Number T32-AG000186 (Hendren).

(SSI), and $30 billion for cash welfare (TANF).[1] How much would recipients be willing to pay for Medicaid and how does this compare to Medicaid's costs? And how much of Medicaid's costs reflect a monetary transfer to non-recipients who bear some of the costs of covering the low-income uninsured?

There is a voluminous academic literature studying the reduced-form impacts of Medicaid on a variety of potentially welfare-relevant outcomes – including health care use, health, and risk exposure. But, there has been little formal attempt to translate such estimates into statements about welfare. Absent other guidance, academic or public policy analyses often either ignore the value of Medicaid – for example, in the calculation of the poverty line or measurement of income inequality (Gottschalk and Smeeding (1997)[33]) – or makes ad hoc assumptions. For example, the Congressional Budget Office (2012)[48] values Medicaid at the average government expenditure per recipient. In practice, an in-kind benefit like Medicaid may be valued above or below its costs (see, e.g., Currie and Gahvari (2008)[17]).

The 2008 Oregon Health Insurance Experiment provided estimates from a randomized evaluation of the impact of Medicaid coverage for low-income, uninsured adults on a range of potentially welfare-relevant outcomes. The main findings from the first two years were: Medicaid increased health care use across the board – including outpatient care, preventive care, prescription drugs, hospital admissions, and emergency room visits; Medicaid improved self-reported health, and reduced depression, but had no statistically significant impact on mortality or physical health measures; Medicaid reduced the risk of large out-of-pocket medical expenditures; and Medicaid had no economically or statistically significant impact on employment and earnings, or on private health insurance coverage (Finkelstein et al. (2012)[28], Baicker et al. (2013)[6], Taubman et al. (2014)[47], Baicker et al. (2014)[4], and Finkelstein et al. (2016)[29]). These results have attracted considerable attention. But in the absence of any formal welfare analysis, it has been left to partisans and media pundits to opine (with varying conclusions) on the welfare implications of

[1] See Department of Health and Human Services (2015, 2016)[50, 51], Department of Agriculture (2016)[49], Internal Revenue Service (2015)[52], and Social Security Administration (2016)[53]).

these findings.[2]

Empirical welfare analysis is challenging when the good in question – in this case public health insurance for low-income adults – is not traded in a well-functioning market. This prevents welfare analysis based on estimates of ex-ante willingness to pay derived from contract choices, as is becoming commonplace where private health insurance markets exist (Einav, Finkelstein, and Levin (2010)[23] provide a review). Instead, one encounters the classic problem of valuing goods when prices are not observed (Samuelson (1954)[46]).

We develop frameworks for empirically estimating the value of Medicaid to recipients in terms of the amount of current, non-medical consumption they would need to give up to be indifferent between receiving Medicaid or not; we refer to this as the recipient's "willingness to pay" for Medicaid. We focus on this normative measure because it is well defined even if individuals are not optimizing when making healthcare decisions. This allows us to incorporate various frictions - such as information frictions or behavioral biases - that could alter the individual's value of Medicaid relative to what a compensating variation approach would imply. Our approach, however, only speaks directly to the *recipient's* willingness to pay for Medicaid. An estimate of *society's* willingness to pay for Medicaid needs to take account of the social value of any redistribution that occurs through Medicaid; and, as is well known, such redistribution generally involves net resource costs that exceed the recipient's willingness to pay (Okun (1975) [44]).

We develop two main analytical frameworks for estimating recipient willingness to pay for Medicaid. Our first approach, which we refer to as the "complete-information" approach, requires a complete specification of a normative utility function and estimates of the causal effect of Medicaid on the distribution of all arguments of the utility function. The advantage of this approach

[2]The results of the Oregon Health Insurance Experiment received extensive media coverage, but the media drew a wide variety of conclusions as the following two headlines illustrate: "Medicaid Makes 'Big Difference' in Lives, Study Finds" (National Public Radio, 2011, http://www.npr.org/2011/07/07/137658189/medicaid-makes-big-difference-in-lives-study-finds) versus "Spending on Medicaid doesn't actually help the poor" (Washington Post, 2013, http://www.washingtonpost.com/blogs/right-turn/wp/2013/05/02/spending-on-medicaid-doesnt-actually-help-the-poor/). Public policy analyses have drawn similarly disparate conclusions: "Oregon's lesson to the nation: Medicaid Works" (Oregon Center for Public Policy, 2013, http://www.ocpp.org/2013/05/04/blog20130504-oregon-lesson-nation-medicaid-works/) versus "Oregon Medicaid Study Shows Michigan Medicaid Expansion Not Worth the Cost" (MacKinac Center for Public Policy, 2013, http://www.mackinac.org/18605).

is that it does not require us to model the precise budget set created by Medicaid or impose that individuals optimally consume medical care subject to this budget constraint. However, as the name implies, the information requirements are high; it will fail to accurately measure the value of Medicaid unless the impacts of Medicaid on *all* arguments of the utility function are specified and analyzed.

Our second approach, which we refer to as the "optimization" approach, is in the spirit of the "sufficient statistics" approach described by Chetty (2009)[13], and is the mirror image of the complete-information approach in terms of its strengths and weaknesses. We reduce the implementation requirements by parameterizing the way in which Medicaid affects the individual's budget set, and by assuming that individuals have the ability and information to make privately optimal choices with respect to that budget set. With these assumptions, it suffices to specify the marginal utility function over any single argument. This is because the optimizing individual's first-order condition allows us to value marginal impacts of Medicaid on any other potential arguments of the utility function through the marginal utility of that single argument. To make inferences about non-marginal changes in an individual's budget set (i.e., covering an uninsured individual with Medicaid), we require an additional statistical assumption that allows us to interpolate between local estimates of the marginal impact of program generosity. This substitutes for the structural assumptions about the utility function in the complete-information approach.

We implement these approaches for the Medicaid coverage provided by the Oregon Health Insurance Experiment. We use data from study participants to directly measure out-of-pocket medical spending, health care utilization, and health. The lottery's random selection allows for causal estimates of the impact of Medicaid on the various outcomes. Our baseline health measure is a mapping of self-assessed health into quality-adjusted of life years (QALYs) based on existing estimates of QALYs associated with different levels of self-assessed health; we also report estimates based on alternative health measures - such as self-reported physical and mental health, or a depression screen - combined with existing estimates of their associated QALYs. Absent a consumption survey in the Oregon context, we proxy for consumption by the difference between average consumption for a low-income uninsured population and out-of-pocket medical expenditures reported by study participants, subject to a consumption floor; we also report results that instead use consumption data for a low-income sample in the Consumer Expenditure Survey.

Our results reveal that Medicaid is best conceived of as consisting of two separate parts: a monetary transfer to external parties who would otherwise subsidize the medical care for the low-income uninsured, and a subsidized insurance product for recipients. The experimental treatment effects of Medicaid on out-of-pocket spending and total medical spending imply that 60% of Medicaid's gross expenditures - which we estimate to be $3,600 per recipient - are a transfer to these external parties, leaving the net cost of Medicaid at about $1,450 per recipient. Recipient willingness to pay for Medicaid could exceed this net cost due to the pure-insurance value it provides (reallocation towards states of the world with high marginal utility), or could be less than its net cost due to recipients' moral hazard response (induced medical spending valued below cost). Our different approaches reach different conclusions: willingness to pay for Medicaid by recipients per dollar of net cost ranges between $0.5 to $1.2; all approaches suggest that recipient willingess to pay for Medciaid is substantially below its *gross* cost (the value of Medicaid assumed by the Congressional Budget Office (2012)[48]). For the approaches that provide point estimates of the sources of Medicaid's value to recipients, we estimate that between half and four-fifths of Medicaid's value to recipients comes from the increase in expected resources it provides rather than from its (budget-neutral) insurance value. Naturally, our estimates are specific to this particular Medicaid program for low-income adults and to the people for whom the lottery affected Medicaid coverage. Yet, the frameworks we develop can be readily applied to welfare analysis of other public health insurance programs, such as Medicaid coverage for other populations or Medicare coverage.

Our analysis complements other efforts to elicit a value of Medicaid to recipients through quasi-experimental variation in premiums (e.g., Dague (2014)[20])) or the extent to which individuals distort their labor earnings in order to become eligible for Medicaid (Gallen (2014)[30], Keane and

Moffitt (1998)[37]).[3] These alternative approaches require their own, different sets of assumptions. Consistent with our results, these approaches also tend to indicate that Medicaid recipients place a low value on the program relative to the government's gross cost of providing Medicaid. However, they do not generally estimate the monetary transfers to external parties or compare recipient value to net (of these monetary transfers) costs. Our finding that a large part of Medicaid spending represents a transfer to external parties complements related empirical work documenting the presence of implicit insurance for the uninsured (Mahoney (2015))[40] and the role of formal insurance coverage in reducing the provision of uncompensated care by hospitals (Garthwaite et al. (2018)[32]) and unpaid medical bills by patients (Dobkin et al. (2018)[21]). Given the size of these external monetary transfers relative to Medicaid's value to recipients, our findings suggest identifying the ultimate economic incidence of uncompensated care and assessing the relative efficiency of formal public insurance versus an informal insurance system of uncompensated care are important areas for further work.

The rest of the paper proceeds as follows. Section 2 develops the two theoretical frameworks for welfare analysis. Section 3 describes how we implement these frameworks for welfare analysis of the impact of the Medicaid expansion that occurred via lottery in Oregon. Section 4 presents the results, discusses their interpretations, and discusses the tradeoffs in our context across the alternative approaches. The last section concludes.

2 Frameworks for Welfare Analysis

2.1 A simple model of individual utility

Individuals derive utility from the consumption of non-medical goods and services, c, and from health, h, according to:

$$u = u(c, h). \tag{1}$$

[3] Finkelstein, Hendren, and Shepard (2017)[26] use variation in premiums for health insurance in Massachusetts to study the value of subsidized health insurance for low-income adults above the Medicaid eligibility threshold.

We assume health is produced according to:

$$h = \tilde{h}(m; \theta), \tag{2}$$

where m denotes the consumption of medical care and θ is an underlying state variable for the individual which includes medical conditions and other factors affecting health, and the productivity of medical spending. This framework is similar to Cardon and Hendel (2001) [11]. We normalize the resource costs of m and c to unity so that m represents the true resource cost of medical care. For the sake of brevity, we will refer to m as "medical spending" and c as "consumption."

We assume every Medicaid recipient faces the same distribution of θ. Conceptually, our welfare analysis can be thought of as conducted from behind the veil of ignorance (conditional on being a low-income adult). Empirically, we will use the distribution of outcomes across individuals to measure the distribution of potential states of the world, θ.

We denote the presence of Medicaid by the variable q, with $q = 1$ indicating that the individual is covered by Medicaid ("insured") and $q = 0$ denoting not being covered by Medicaid ("uninsured"). Consumption, medical spending, and health outcomes depend both on Medicaid status, q, and the underlying state of the world, θ; this dependence is denoted by $c(q;\theta)$, $m(q;\theta)$ and $h(q;\theta) \equiv \tilde{h}(m(q;\theta);\theta)$, respectively.[4]

We define $\gamma(1)$ as the amount of consumption that the individual would need to give up in the world with Medicaid that would leave her at the same level of expected utility as in the world without Medicaid:

$$E[u(c(0;\theta), h(0;\theta))] = E[u(c(1;\theta) - \gamma(1), h(1;\theta))], \tag{3}$$

where the expectations are taken with respect to the possible states of the world, θ. With some abuse of terminology, we will refer to $\gamma(1)$ as the recipient's willingness to pay for Medicaid even

[4] We assume that q affects health only through its effect on medical spending. This rules out an impact of insurance, q, on non-medical health investments as in Ehrlich and Becker (1972)[22].

though it is measured in terms of forgone consumption rather than forgone income.

Importantly, $\gamma(1)$ is measured from the perspective of the individual recipient. A social welfare perspective would also account for the fact that Medicaid benefits a low-income group. Saez and Stantcheva (2016)[45] show that in general this can be accomplished by scaling the individual valuation by a social marginal welfare weight, or the social marginal utility of income. For example, suppose the social marginal utility of income of Medicaid beneficiaries is twenty times as high as the social marginal utility of income of the average person in the population. Then, society is willing to pay \$20 to deliver \$1 to a Medicaid beneficiary. To move from our estimates of the recipient's willingness to pay for Medicaid to society's willingness to pay, one would therefore scale our estimates of $\gamma(1)$ by 20; we return to this point in Section 4.3.

2.2 Complete-information approach

In the complete-information approach, we specify the normative utility function over all its arguments and require that we observe all these both with insurance and without insurance. It is then straightforward to solve equation (3) for $\gamma(1)$.

Assumption 1. *(Full utility specification for the complete-information approach) The utility function takes the form:*

$$u(c,h) = \frac{c^{1-\sigma}}{1-\sigma} + \tilde{\phi}h,$$

where σ denotes the coefficient of relative risk aversion and $\tilde{\phi}$ denotes the marginal utility of health. Scaling $\tilde{\phi}$ by the expected marginal utility of consumption yields the expected marginal rate of substitution of health for consumption, ϕ $\left(= \tilde{\phi}/E[c^{-\sigma}]\right)$.

Utility has two additive components: a standard CRRA function in consumption c with a coefficient of relative risk aversion of σ, and a linear term in h. The assumption that utility is linear in health is consistent with our measure of health (quality-adjusted life years, introduced below), which by construction is linear in utility. The assumption that consumption and health are additive is commonly made in the health literature, but restricts the marginal utility of consumption to be independent of health. This assumption simplifies the implementation of our estimates (though our framework could in principle be applied with non-additive functions).

With this assumption, equation (3) becomes, for $q = 1$:

$$E\left[\frac{c(0;\theta)^{1-\sigma}}{1-\sigma} + \tilde{\phi} h(0;\theta)\right] = E\left[\frac{(c(1;\theta)-\gamma(1))^{1-\sigma}}{1-\sigma} + \tilde{\phi} h(1;\theta)\right], \tag{4}$$

and we can use equation (4) to solve for $\gamma(1)$. This requires observing the distribution of consumption and expected health that occur if the individual were on Medicaid ($c(1;\theta)$ and $E[h(1;\theta)]$) and if he were not ($c(0;\theta)$ and $E[h(0;\theta)]$). One of these is naturally counterfactual. We are therefore in the familiar territory of estimating the distribution of "potential outcomes" under treatment and control (e.g., Angrist and Pischke (2009) [1]).

We can decompose $\gamma(1)$ into two economically distinct components: the increases in average resources for the individual, and the (budget-neutral) reallocation of resources across states of the world. We refer to these as, respectively, the "transfer component" (T) and the "pure-insurance component" (I). The transfer component is given by the solution to the equation:

$$\frac{E[c(0;\theta)]^{1-\sigma}}{1-\sigma} + \tilde{\phi} E\left[\tilde{h}(E[m(0;\theta)];\theta)\right] = \frac{(E[c(1;\theta)]-T)^{1-\sigma}}{1-\sigma} + \tilde{\phi} E\left[\tilde{h}(E[m(1;\theta)];\theta)\right]. \tag{5}$$

Approximating the health improvement $E\left[\tilde{h}(E[m(1;\theta)];\theta) - \tilde{h}(E[m(0;\theta)];\theta)\right]$ by $E\left[\frac{d\tilde{h}}{dm}\right] E[m(1;\theta) - m(0;\theta)]$, we implement the calculation of T as the implicit solution to:

$$\frac{E[c(0;\theta)]^{1-\sigma}}{1-\sigma} - \frac{(E[c(1;\theta)]-T)^{1-\sigma}}{1-\sigma} = \tilde{\phi} E\left[\frac{d\tilde{h}}{dm}\right] E[m(1;\theta) - m(0;\theta)]. \tag{6}$$

Medicaid spending that increases consumption (c) increases T dollar-for-dollar; however, increases in medical spending (m) due to Medicaid may increase T by more or less than a dollar depending on the health returns to medical spending as described by the health production function, $\tilde{h}(m;\theta)$.[5] Relatedly, evaluating this equation requires an estimate of $E\left[\frac{d\tilde{h}}{dm}\right]$, the slope of the

[5] By the standard logic of moral hazard, if consumers optimally choose m, they would value the increase in health

health production function between $m(1;\theta)$ and $m(0;\theta)$, averaged over all states of the world.

The pure-insurance term (I) is given by:

$$I = \gamma(1) - T. \tag{7}$$

The pure-insurance value will be positive if Medicaid moves resources towards states of the world with a higher marginal utility of consumption and a higher health return to medical spending.

2.3 Optimization approaches

In the optimization approaches, we reduce the implementation requirements of the complete-information approach through two additional economic assumptions: We assume that Medicaid affects individuals only through its impact on their budget constraint, and we assume individual optimizing behavior. These two assumptions allow us to replace the full specification of the utility function (Assumption 1) by a partial specification of the utility function.

Assumption 2. *(Program structure) We model the Medicaid program q as affecting the individual solely through its impact on the out-of-pocket price for medical care $p(q)$.*

This assumption rules out other ways in which Medicaid might affect c or h, such as through an effect of Medicaid on a provider's willingness to treat a patient. For implementation purposes, we assume that $p(q)$ is constant in m although, in principle, we could allow for a nonlinear price schedule. We denote out-of-pocket spending on medical care by:

$$x(q,m) \equiv p(q)m. \tag{8}$$

We do not impose that those without Medicaid pay all their medical expenses out of pocket (i.e., $p(0) = 1$), thus allowing for implicit insurance for the uninsured.

arising from the Medicaid-induced medical spending at less than its cost, since they chose not to purchase that medical spending at an unsubsidized price. Note, however, that we have not (yet) imposed consumer optimization.

Assumption 3. *(Individual optimization) Individuals choose m and c optimally, subject to their budget constraint. Individuals solve:*

$$\max_{c,m} u\left(c, \tilde{h}(m;\theta)\right) \text{ subject to } c = y(\theta) - x(q,m) \quad \forall m, q, \theta,$$

where $y(\theta)$ denotes (potentially state-contingent) resources.

The assumption that the choices of c and m are individually optimal is a nontrivial assumption in the context of health care where decisions are often taken jointly with other agents (e.g., doctors) who may have different objectives (Arrow (1963)[2]) and where the complex nature of the decision problem may generate individually suboptimal decisions (Baicker, Mullainathan, and Schwartzstein (2015)[5]).

Under these two assumptions, we consider the thought experiment of a "marginal" expansion in Medicaid. In this thought experiment, q indexes a linear coinsurance term between no Medicaid ($q = 0$) and "full" Medicaid ($q = 1$), so that we can define $p(q) \equiv qp(1) + (1-q)p(0)$. Out-of-pocket spending in equation (8) is now:

$$x(q,m) = qp(1)m + (1-q)p(0)m. \tag{9}$$

A marginal expansion of Medicaid (i.e., a marginal increase in q), relaxes the individual's budget constraint by $-\frac{\partial x}{\partial q}$:

$$-\frac{\partial x(q, m(q;\theta))}{\partial q} = (p(0) - p(1))m(q;\theta). \tag{10}$$

The marginal relaxation of the budget constraint is thus the marginal reduction in out-of-pocket spending at the current level of m. It therefore depends on medical spending at q, $m(q;\theta)$, and the price reduction from moving from no insurance to Medicaid, $(p(0) - p(1))$. Note that $-\frac{\partial x}{\partial q}$ is a program parameter that holds behavior (m) constant.

We define $\gamma(q)$ – in parallel fashion to $\gamma(1)$ in equation (3) – as the amount of consumption the individual would need to give up in a world with q insurance that would leave her at the same level of expected utility as with $q=0$:

$$E\left[u\left(c\left(0;\theta\right),h\left(0;\theta\right)\right)\right]=E\left[u\left(c\left(q;\theta\right)-\gamma(q),h\left(q;\theta\right)\right)\right]. \tag{11}$$

2.3.1 Consumption-based optimization approach

If individuals choose c and m to optimize their utility function subject to their budget constraint (Assumptions 2 and 3), the marginal impact of insurance on recipient willingness to pay ($\frac{d\gamma}{dq}$) follows from applying the envelope theorem to equation (11):

$$\frac{d\gamma}{dq}=E\left[\frac{u_c}{E\left[u_c\right]}\left(\left(p(0)-p(1)\right)m(q;\theta)\right)\right], \tag{12}$$

where u_c denotes the partial derivative of utility with respect to consumption. Appendix A.1 provides the derivation. Note that the optimization approaches do not require us to estimate how the individual allocates the marginal relaxation of the budget constraint between increased consumption and health. Because the individual chooses consumption and health optimally (Assumption 3), a marginal reallocation between consumption and health has no first-order effect on the individual's utility.

The representation in equation (12), which we call the *"consumption-based optimization approach,"* uses the marginal utility of consumption to place a value on the relaxation of the budget constraint in each state of the world. In particular, $\frac{u_c}{E[u_c]}$ measures the value of money in each state of the world relative to its average value, and $((p(0)-p(1))m(q;\theta))$ measures how much a marginal expansion in Medicaid relaxes the individual's budget constraint in each state of the world. A marginal increase in Medicaid benefits delivers greater value if it moves more resources into states of the world, θ, with a higher marginal utility of consumption (e.g., states of the world with larger medical bills, and thus lower consumption). As we discuss in Appendix A.1, this approach allows individuals to be at a corner with respect to their choice of medical spending.

We can decompose the marginal value of Medicaid to recipients in equation (12) into a transfer term (T) and a pure-insurance term (I):

$$\frac{d\gamma(q)}{dq} = \underbrace{(p(0)-p(1))E\left[m(q;\theta)\right]}_{\text{Transfer Term}} + \underbrace{Cov\left[\frac{u_c}{E\left[u_c\right]},(p(0)-p(1))m(q;\theta)\right]}_{\substack{\text{Pure-Insurance Term} \\ \text{(consumption valuation)}}}. \tag{13}$$

Although implemented differently, the transfer and pure-insurance term are conceptually the same as in the complete-information approach above. The transfer term measures the recipients' valuation of the expected transfer of resources from the rest of the economy to them. Optimization implies this value cannot exceed the cost of the transfer and will be below this cost due to the moral hazard response to insurance. The "pure-insurance" term measures the benefit of a budget-neutral reallocation of resources across different states of the world, θ. The movement of these resources is valued using the marginal utility of consumption in each state. The pure-insurance term will be positive for risk-averse individuals as long as Medicaid re-allocates resources to states of the world with higher marginal utilities of consumption.

We integrate $\frac{d\gamma}{dq}$ from $q=0$ to $q=1$ to arrive at a non-marginal estimate of the recipient's total willingness to pay for Medicaid, $\gamma(1)$, noting that $\gamma(0)=0$:

$$\begin{aligned} \gamma(1) &= \int_0^1 \frac{d\gamma(q)}{dq}dq \\ &= \underbrace{(p(0)-p(1))\int_0^1 E[m(q;\theta)]dq}_{\text{Transfer Term}} + \underbrace{\int_0^1 Cov\left(\tfrac{u_c}{E[u_c]},(p(0)-p(1))m(q;\theta)\right)dq}_{\substack{\text{Pure-Insurance Term} \\ \text{(consumption valuation)}}} \end{aligned} \tag{14}$$

We estimate the transfer term and pure-insurance term separately, and then combine them.

Implementation

Evaluation of the transfer term in equation (13) does not require any assumptions about the utility function. However, integration in equation (14) to obtain an estimate of the transfer term requires that we know the path of $m(q;\theta)$ for interior values of q, which are not directly observed. For our baseline implementation, we make the following statistical assumption:

Assumption 4. *(Linear approximation) The integral expression for $\gamma(1)$ in equation (14) is well approximated by:*

$$\gamma(1) \approx \frac{1}{2}\left[\frac{d\gamma(0)}{dq} + \frac{d\gamma(1)}{dq}\right].$$

While we use this assumption for our baseline results, we can bound the transfer term without it. Under the natural assumption that average medical spending under partial insurance lies between average medical spending under full insurance and average medical spending under no insurance (i.e., $E[m(0;\theta)] \leq E[m(q;\theta)] \leq E[m(1;\theta)]$), we obtain the following lower and upper bounds:

$$[p(0)-p(1)]E[m(0;\theta)] \leq (p(0)-p(1))\int_0^1 \frac{E[m(q;\theta)]}{dq}dq \leq [p(0)-p(1)]E[m(1;\theta)]. \quad (15)$$

While the transfer term does not require specification of a utility function, evaluation of the pure-insurance term in equation (13) requires specifying the marginal utility of consumption. To do so, we assume the utility function takes the following form:

Assumption 5. *(Partial utility specification for the consumption-based optimization approach) The utility function takes the following form:*

$$u(c,h) = \frac{c^{1-\sigma}}{1-\sigma} + v(h)$$

where σ denotes the coefficient of relative risk aversion and $v(.)$ is the subutility function for health, which can be left unspecified.

The pure-insurance term in equation (13) can then be rewritten as:

$$Cov\left(\frac{c\,(q;\theta)^{-\sigma}}{E[c\,(q;\theta)^{-\sigma}]},(p(0)-p(1))m(q;\theta)\right). \tag{16}$$

We can use the above equations to calculate the marginal value of the first and last units of insurance ($\frac{d\gamma(0)}{dq}$ and $\frac{d\gamma(1)}{dq}$ respectively). Assumption 4 then allows us to use estimates of $\frac{d\gamma}{dq}(0)$ and $\frac{d\gamma}{dq}(1)$ to form estimates of $\gamma(1)$.

2.3.2 Health-based optimization approach

The consumption-based optimization approach values Medicaid by how it relaxes the budget constraint in states of the world with different marginal utilities of consumption. One can alternatively value Medicaid by how it relaxes the budget constraint in states of the world with different marginal utilities of out-of-pocket spending on health.

This requires a stronger assumption than Assumption 3, which states that individuals optimize; we now require that individual choices of m and c satisfy a first-order condition:

Assumption 6. *(First-order condition holds) The individual's choices of m and c are at an interior optimum and hence satisfy the first-order condition:*

$$u_c\,(c,h)\,p(q) = u_h\,(c,h)\,\frac{d\tilde{h}(m;\theta)}{dm} \quad \forall m,q,\theta. \tag{17}$$

The left-hand side of equation (17) is the marginal cost of medical spending operating through forgone consumption. The right-hand side of equation (17) is the marginal benefit of additional medical spending, which equals the marginal utility of health, $u_h\,(c,h)$, multiplied by the increase in health provided by additional medical spending, $\frac{d\tilde{h}}{dm}$.

We use equation (17) to replace the marginal utility of consumption, u_c in equation (12) with a term depending on the marginal utility of health, u_h, yielding:

$$\frac{d\gamma}{dq} = E\left[\left(\frac{u_h}{E\,[u_c]}\frac{d\tilde{h}(m;\theta)}{dm}\frac{1}{p(q)}\right)((p(0)-(p(1))m(q;\theta))\right]. \tag{18}$$

We refer to equation (18) as the *"health-based optimization approach."* The term $\frac{u_h}{E[u_c]}\frac{d\tilde{h}(m;\theta)}{dm}\frac{1}{p(q)}$ measures the value of money in each state of the world relative to its average value and the term $(p(0)-(p(1))m(q;\theta)$ measures how much Medicaid relaxes the individual's budget constraint in the current state of the world. From the health-based optimization approach's perspective, the program delivers greater value if it moves more resources to states of the world with a greater return to out-of-pocket spending.[6]

The marginal value of Medicaid to recipients in equation (18) can be decomposed into a transfer term and a pure-insurance term:

$$\frac{d\gamma(q)}{dq} = \underbrace{(p(0)-p(1))E\left[m(q;\theta)\right]}_{\text{Transfer Term}} + \underbrace{Cov\left(\frac{u_h}{E\left[u_c\right]}\frac{d\tilde{h}(m;\theta)}{dm}\frac{1}{p(q)},(p(0)-(p(1))m(q;\theta)\right)}_{\substack{\text{Pure-Insurance Term} \\ \text{(health valuation)}}}. \tag{19}$$

Implementation

Since the transfer term does depend on the utility function, it is the same as the transfer term in the consumption-based optimization approach. However, evaluation of the pure-insurance term requires a partial specification of the utility function:

Assumption 7. *(Partial utility specification for the health-based optimization approach) The utility function takes the following form:*

$$u(c,h) = \tilde{\phi}h + \tilde{v}(c),$$

where $\tilde{v}(.)$ is the subutility function for consumption, which can be left unspecified.

[6] Unlike the consumption-based optimization approach, the health-based optimization approach will be biased if individuals are at a corner solution in medical spending, so that they are not indifferent between an additional \$1 of medical spending and an additional \$1 of consumption. In this case, the first term between parentheses in equation (18) is less than the true value that the individual puts on money in that state of the world (i.e., $\left(\frac{u_h}{E[u_c]}\frac{d\tilde{h}(m;\theta)}{dm}\frac{1}{p(q)}\right) < \frac{u_c}{E[u_c]}$), generating upward bias in the covariance term in equation (19) below because $(p(0)-p(1))m$ is below its mean at the corner solution $m=0$.

Assumption 7 allows us to write the pure-insurance term in the health-based optimization approach in equation (19) as:

$$Cov\left(\frac{d\tilde{h}(m;\theta)}{dm}\frac{\phi}{p(q)}, (p(0)-(p(1))m(q;\theta)\right). \tag{20}$$

The term $\phi \equiv \frac{\tilde{\phi}}{E[\tilde{v}'(c)]}$ is the marginal rate of substitution of health for consumption, as in the complete-information approach. Implementation of equation (20) requires that we estimate variation across states of the world in the marginal health return to medical spending, $\frac{d\tilde{h}}{dm}$. As with the consumption-based optimization approach, we estimate $\gamma(1)$ as the average of $\frac{d\gamma(0)}{dq}$ and $\frac{d\gamma(1)}{dq}$ using the linear approximation in Assumption 4.

2.3.3 Comment: Endless Arguments

A key distinction between the complete-information and the optimization approaches is that the optimization approaches allow one to consider marginal utility with respect to *one* argument of the utility function. In contrast, the complete-information approach requires "adding up" the impact of Medicaid on *all* arguments of the utility function. In the above model, we assumed the only arguments were consumption and health. If we were to allow other potentially utility-relevant factors that Medicaid could affect (such as leisure, future consumption, or children's outcomes, or even hassle costs when dealing with medical providers as an uninsured patient), we would also need to estimate the impact of Medicaid on these arguments, and value these changes by the marginal utilities of these goods across states of the world. As a result, there is a potential methodological bias to the complete-information approach; one can keep positing potential arguments that Medicaid affects if one is not yet satisfied by the welfare estimates.

2.4 Gross and net costs

We benchmark our estimates of $\gamma(1)$ against Medicaid costs. We consider only medical expenditures when estimating program costs. This abstracts from potential administrative costs and from any labor supply responses to Medicaid, both of which could impose fiscal externalities on the government.[7] Under these assumptions, the average cost to the government per recipient, which we denote by G, is given by:

$$G = E\left[m(1;\theta) - x(1, m(1;\theta))\right]. \tag{21}$$

This gross cost per recipient, G, may be higher than the net resource cost to society; some component of Medicaid spending may replace costs previously borne by external parties (non-recipients).

Medicaid's net resource cost per recipient, which we denote by C, is given by:

$$C = E\left[m(1;\theta) - m(0;\theta)\right] + E\left[x(0, m(0;\theta)) - x(1, m(1;\theta))\right]. \tag{22}$$

Net cost per recipient consists of the average increase in medical spending induced by Medicaid, $m(1;\theta) - m(0;\theta)$, plus the average decrease in out-of-pocket spending due to Medicaid, $x(0, m(0;\theta)) - x(1, m(1;\theta))$.

We decompose gross costs to the government, G, into net costs, C, and monetary transfers to external parties who provide implicit insurance to the uninsured N:

$$G = C + N.$$

The monetary transfers to external parties (N) are given by:

$$N = E\left[m(0;\theta)\right] - E\left[x(0, m(0;\theta))\right]. \tag{23}$$

2.5 Summary: Required empirical objects

Table 1 summarizes the empirical objects we need for each approach, highlighting the key trade-offs across approaches in terms of objects that need to be estimated and parameters that need to

[7] In the context of the Oregon Health Insurance Experiment, there is no evidence that Medicaid affected labor market activities (Baicker et al. (2014)[4]).

be calibrated. Estimating costs and transfers to external parties (G, C and N) requires the same two objects for all three approaches: mean out-of-pocket spending and mean medical spending, both with and without Medicaid. The complete-information approach further requires estimates of mean health outcomes with and without Medicaid and the distribution of consumption with and without Medicaid. It also requires two calibrated parameters of the utility function: one to value health outcomes (ϕ) and one to value consumption outcomes (σ). By contrast, the optimization approaches require *either* estimates of distribution of the health returns to medical spending and one calibrated parameter (ϕ) *or* information on the distribution of consumption, with and without Medicaid, and one calibrated parameter (σ). In addition, the optimization-based approaches both require the out-of-pocket price of Medicaid, and the distribution of out-of-pocket spending, with and without Medicaid.

3 Application: The Oregon Health Insurance Experiment

We apply these approaches to the Medicaid expansion that occurred in Oregon in 2008 via a lottery. The Medicaid expansion covered low-income (below 100 percent of the federal poverty line), uninsured adults (aged 19-64) who were not already categorically eligible for Medicaid. The expansion provided comprehensive medical benefits with no patient cost-sharing and no or low monthly premiums. We focus on the effects of Medicaid coverage after approximately one year.

We use this setting to implement the complete-information approach, and two different variants of the consumption-based optimization approach. In the working paper version (Finkelstein et al. 2015[25]), we also implemented the health-based optimization approach, and found we lacked the statistical power to credibly estimate heterogeneity in the return to medical spending, $\frac{d\tilde{h}}{dm}$, and hence the pure-insurance component (I) (see equation (20)).

3.1 Empirical approach

In early 2008, the state opened a waiting list for the Medicaid expansion and then randomly selected 30,000 of the 75,000 people on the waiting list to be able to apply for Medicaid. Following the approach of previous work on the Oregon experiment, we use random assignment by the lottery as an instrument for Medicaid. As a result, all of our estimates of the impact of Medicaid are local average treatment effects (LATEs) of Medicaid for the compliers - i.e., those who are covered by Medicaid if and only if they win the lottery. Thus in our application, "the insured" $(q = 1)$ are treatment compliers and "the uninsured" $(q = 0)$ are control compliers. More details can be found in Appendix A.2.

The data from the Oregon Health Insurance Experiment are publicly available at www.nber.org/oregon. Data on Medicaid coverage (q) are taken from state administrative records. In our baseline analysis, all other data elements from the Oregon Health Insurance Experiment come from mail surveys sent about one year after the lottery to individuals who signed up for the lottery. Table 2 presents descriptive statistics from this mail survey. Panel A presents demographic information. The population is 60 percent female and 83 percent white; about one-third are between the ages of 50-64. The demographic characteristics are balanced between treatment and control compliers (p-value = 0.12). Panel B presents summary statistics on key outcome measures in the Oregon data; we now discuss their construction.

3.2 Medical spending , out-of-pocket spending , and out-of-pocket prices

Medical spending *m*. Survey responses provide measures of utilization of prescription drugs, outpatient visits, ER visits, and inpatient hospital visits. To turn these into spending estimates, Finkelstein et al. (2012)[28] annualized the utilization measures and summed them up, weighting each type by its average cost (expenditures) among low-income publicly insured non-elderly adults in the Medical Expenditure Survey (MEPS).[8]

[8]The MEPS data on expenditures reflect actual payments (i.e., transacted prices) rather than contract or list prices (MEPS (2013), page C-107)[41]).

We estimate that Medicaid increases total medical spending by about \$900. On average, annual medical spending is about \$2,700 for control compliers ($q = 0$) and \$3,600 for treatment compliers ($q = 1$).

Out-of-pocket spending x**.** We measure annual out-of-pocket spending for the uninsured ($q = 0$) based on self-reported out-of-pocket medical expenditures in the last six months, multiplied by two.[9] Average annual out-of-pocket medical expenditures for control compliers is $E\left[(x(0,m(0,\theta))\right] = \$569$.

Our baseline analysis assumes that the insured have zero out-of-pocket spending (i.e., $x(1,m(1;\theta)) = 0$). We make this assumption because Medicaid in Oregon has zero out-of-pocket cost sharing, no or minimal premiums, and comprehensive benefits.[10] However, the insured do report positive spending, and we explore sensitivity to using these reports for $x(1,m(1;\theta))$; naturally, this reduces our estimate of the value of Medicaid to recipients.

Out-of-pocket prices p**.** The optimization approaches require that we define the out-of-pocket price of medical care with Medicaid, $p(1)$, and without Medicaid, $p(0)$. Our baseline analysis assumes $p(1) = 0$; i.e., those with Medicaid pay nothing out of pocket towards medical spending. We measure $p(0)$ as the ratio of mean out-of-pocket spending to mean total medical spending for control compliers ($q = 0$), i.e., $\frac{E[x(0,m(0;\theta))]}{E[m(0;\theta)]}$. We estimate $p(0) = 0.21$, which implies that the uninsured pay only about \$0.2 on the dollar for their medical spending, with the remainder of the uninsured's expenses being paid by external parties. This is consistent with estimates from other

[9] To be consistent with our treatment of out-of-pocket spending when we use it to estimate consumption (discussed below in subsection 3.4), we impose two adjustments. First, we fit a log normal distribution on the out-of-pocket spending distribution. Second, we impose a per capita consumption floor by capping out-of-pocket spending so that per capita consumption never falls below the floor.

[10] This assumes that the uninsured report their out-of-pocket spending without error but that the insured (some of whom report positive out-of-pocket spending in the data) do not. This is consistent with a model of reporting bias in which individuals are responding to the survey with their typical out-of-pocket spending, not the precise spending they have incurred since enrolling in Medicaid. In this instance, there would be little bias in the reported spending for those who are not enrolled in Medicaid (since nothing changed), but the spending for those recently enrolled due to the lottery would be dramatically overstated because of recall bias.

contexts.[11]

3.3 Health (h) inputs

Both the complete-information approach and the health-based optimization approach require that we measure health and that we calibrate individuals' marginal rate of substitution of health for consumption. Our baseline measure of health is the widely-used five-point self-assessed health question that asks "In general, would you say your health is:" and gives the following response options: "Excellent, Very Good, Good, Fair, Poor." We conduct sensitivity analysis to using other measures of health.

A key challenge is how to express changes in a given measure of health in units of consumption. For non-mortality health measures, the standard approach involves two steps: first map these health measures into a cardinal utility scale, expressed in terms of quality-adjusted life years (QALYs), and then scale it by an estimate of the value of a statistical life year (VSLY) to express it in consumption units. The resulting marginal rate of substitution would be valid for a general population. To find the marginal rate of substitution for low-income individuals, we add a third step: we adjust the estimate for the general population to account for higher marginal utility of consumption in a low-income population. Intuitively, low-income populations have a lower willingness to pay out of consumption because they have lower consumption. We discuss these three steps in turn.

Mapping self-assessed health to QALY units. We map our baseline self-assessed health measure into QALYs using the mapping that Van Doorslaer and Jones (2003)[54] estimated. Their mapping employs the widely used "Health Utilities Index Mark 3" scale, which applies the "standard gamble approach" to a random sample of 500 adults from the City of Hamilton, Canada. Specifically, respondents make choices over hypothetical outcomes in order to find the probability

[11] The Kaiser Commission on Medicaid and the Uninsured estimates that the average uninsured person in the U.S. pays only about 20% of their total medical expenses out-of-pocket. (Coughlin et al. (2014)[15], Figure 1). Hadley et al. (2008)[34] estimate that the uninsured pay only 35% of their medical costs expenses out of pocket. In the 2009-2011 MEPS, we estimate that uninsured adults aged 19-64 below 100 percent of the federal poverty line pay about 33% of their medical expenses out of pocket.

υ such that the respondent is indifferent between living in a particular health state and facing a gamble consisting of living in perfect health with probability υ and being dead with probability $1-\upsilon$. One year lived in this particular health state is assigned a QALY of υ. Appendix A.4 provides more detail.

Panel B of Table 2 shows results for our baseline self-assessed health measure, reported in QALY units. Treatment compliers are less likely to respond than control compliers that they are in poor or fair health and more likely to describe their health as good, very good, or excellent. Weighting the effect of Medicaid on each health state by the associated QALY of that health state, our estimates indicate that Medicaid increases health by 0.05 QALYs.

Although QALYs have been frequently used in the economics literature (e.g., Chandra et al. (2011)[12], Cutler et al., (2010)[19], García et al. (2017)[31], and Lakdawalla et al. (2017)[39]), they have the unattractive feature of relying on stated preference. An additional limitation in our setting is that the mapping is estimated on a sample that differ from the population of the Oregon Health Insurance Experiment. To the extent that preferences over a probability of living in perfect health and living for sure in less-than-perfect health are reasonably stable across populations, the mapping will offer a reasonable measure of a quality-adjusted life year.

Choosing a VSLY for a general population. Estimation of the value of a statistical life is also challenging. A large literature, reviewed by Viscusi (1993)[55] and Cropper, Hammitt, and Robinson (2011)[16], uses various approaches to do so. Some, but not all, of these approaches rely on stated-preferences. We take as a "consensus" estimate from this literature Cutler's (2004) [18] choice of $100,000 for the value of a statistical life year (VSLY) for the general US population. In other words, we assume the marginal rate of substitution of health (as measured by QALYs) for consumption to be $100,000 in the general US population.

Adjusting the marginal rate of substitution for a low-income population. Our utility function assumes that the marginal utility of a QALY does not depend on the level of consumption. However, the marginal utility of consumption is higher in a low-income population because of their low levels of consumption, and as a result, the marginal rate of substitution of health for consumption is lower in a low-income population. With CRRA utility over consumption (see Assumption 1), our baseline assumption of a coefficient of relative risk aversion $\sigma = 3$ (see below), and per-capita consumption for our population that is about 40 percent of the general population's (based on our estimates from the Consumer Expenditure Survey), the MRS of health for consumption in our population is approximately 5% ($\approx 0.4^3$) of that in the general population. We therefore use a baseline value of ϕ of $\$5,000$ for our population but report sensitivity to alternative values.

We emphasize that a ϕ of $\$5,000$ reflects the low-income *individual's* willingness to substitute on the margin their *own* consumption for quality-adjusted life years. This does not imply that society's willingness to pay (i.e., reducing *other* people's consumption) for an additional quality-adjusted life year is only $\$5,000$ for low-income populations. We return to this distinction in Section 4.3.

3.4 Consumption (c) inputs

Both the complete-information approach and the consumption-based optimization approach require that we measure consumption. Specifically, the complete-information approach requires that we estimate the impact of Medicaid on the distribution of consumption, while the consumption-based optimization approach requires that we estimate the joint distribution of consumption and out-of-pocket spending for the uninsured to measure the "pure-insurance term".[12] For these approaches, we also need to calibrate a curvature of the utility function. In our baseline analysis, we calibrate the coefficient of relative risk aversion at $\sigma = 3$. Because the Oregon study does not contain consumption data, we take two different approaches to measuring consumption, which we now describe.

[12] Equation (16) suggests that we need to estimate the joint distribution of $c(0;\theta)$ and $(p(0)-p(1))m(0;\theta)$ at $q=0$. Since $p(1)=0$ by assumption, this reduces to the joint distribution of consumption c and out-of-pocket spending $x(0,m(0;\theta)) = p(0)m(0;\theta)$. We need to estimate this joint distribution only for the uninsured (so for $q=0$) because our assumption that Medicaid provides full insurance (i.e., $p(1)=0$) implies that the marginal value of additional insurance for the fully insured (so for $q=1$) is zero.

3.4.1 Consumption proxy approach

We proxy for non-medical per capita consumption c using the individual's out-of-pocket medical spending, x, combined with average values of non-medical expenditure and out-of-pocket medical expenditure. Letting $\bar{c}$ denote the average non-medical expenditure for the population, we define the consumption proxy as:

$$c = \bar{c} - (x - \bar{x})/n, \tag{24}$$

where n denotes family size and $\bar{x}$ denotes average per capita out-of-pocket medical spending among control compliers; average family size among compliers is about 2.9 (see Table 2). Our approach accounts for within-family resource sharing by assuming that consumption is shared equally within the family, i.e., the impact of a given amount of out-of-pocket medical spending on non-medical consumption is shared equally within families.[13] This seems a reasonable assumption given the joint nature of many components of consumption; however, in the sensitivity analysis, we consider that the out-of-pocket spending shock is borne entirely by the individual with the spending.

This consumption proxy approach makes several simplifying assumptions. First, it assumes that the only channel by which Medicaid affects consumption is by reducing out-of-pocket spending; it rules out Medicaid affecting consumption by changing income, which seems empirically reasonable in our context (Finkelstein et al. (2012)[28], Baicker et al. (2014)[4]). Second, it assumes that per capita consumption would be the same for all individuals in the Oregon study if they had the same out-of-pocket spending. This is an assumption made for convenience and unlikely to be literally true. However, it approximates reality to the extent to which heterogeneity in non-medical consumption is limited within our low-income population. Finally, it does not allow

[13] This same logic implies that the benefits from Medicaid are also shared among family members. This is captured in the optimization approach by equation (14); this equation values any dollar flowing to the family by the marginal utility of consumption of the individual irrespective of whether dollar is used to benefit the individual or other family members. However, for the complete-information approach, it requires that we replace $\gamma(1)$ by $\gamma(1)/n$ when estimating equation (3).

for the possibility of any intertemporal consumption smoothing through borrowing or saving. Such opportunities are likely limited in our low-income study population but presumably not zero; by not allowing for this possibility, we likely bias upward our estimate of $\gamma(1)$.

Implementation. We use the Oregon survey data to measure x (as described above), and also family size n. We estimate $\bar{c}$ as mean per capita non-medical consumption in a population that has similar characteristics as participants in the Oregon study, namely families that live below the federal poverty line, have an uninsured household head, and are in the Consumer Expenditure Survey (CEX). To estimate the impact of Medicaid on the distribution of out-of-pocket spending x, we make the parametric assumption that out-of-pocket spending is a mixture of a mass point at zero and a log-normal spending distribution and then estimate the distribution of out-of-pocket spending x for control compliers using standard, parametric quantile IV techniques; see Appendix A.2 for more detail.

Because there is unavoidable measurement error in estimating consumption, and because marginal utility is sensitive to low values of consumption, we rule out implausibly low values of c by imposing an annual consumption floor. Our baseline analysis imposes a consumption floor at the 1st percentile of non-medical consumption for low-income uninsured individuals in the CEX (i.e., \$1,977). We impose the consumption floor by capping the out-of-pocket spending drawn from the fitted log-normal distribution at $\bar{x}+n(\bar{c}-c_{floor})$, where $\bar{x}$ is average per capita out-of-pocket medical spending as in equation (24). Our baseline consumption floor binds for fewer than 0.3 percent of control compliers. In the sensitivity analysis, we explore sensitivity to the assumed value of the consumption floor. Finally, we map the fitted, capped out-of-pocket spending distribution to consumption using equation (24).

Figure 1 shows the resultant distributions of consumption for control compliers ($q=0$) and treatment compliers ($q=1$). Average non-medical consumption for control compliers is \$9,214 with a standard deviation of \$1,089. For treatment compliers, consumption is simply average non-medical consumption for the insured (\$9,505), since by assumption $x(1,m)=0$.[14] The difference

[14] Average non-medical consumption for the low-income uninsured (i.e., $\bar{c}$) is \$9,214 in the CEX. To account for the

between the two lines in the figure shows the increase in consumption due to Medicaid for the compliers.

3.4.2 Consumer Expenditure Survey approach

The consumption proxy approach assumes that changes in out-of-pocket spending x translate one for one into changes in consumption if the individual is above the consumption floor. If individuals can borrow, draw down assets, or have other ways of smoothing consumption, this approach overstates the consumption smoothing benefits of Medicaid. We therefore also employ an alternative approach that uses national data on out-of-pocket spending (x) and non-medical consumption (c) for low-income individuals from the CEX. For the consumption-based optimization approach, the CEX data allow us to directly estimate the pure-insurance term at $q = 0$ in equation (16), i.e., the covariance between the marginal utility of non-medical consumption c and out-of-pocket spending x among the uninsured. Appendix A.5.1 provides more detail on the data, sample definition, and summary statistics in the CEX data and compares the sample of compliers in the Oregon data.

The key advantage of the CEX approach over the consumption proxy approach is the ability to directly observe consumption and its covariance with out-of-pocket spending. But it has two important drawbacks. First, it cannot be used for the complete-information approach because this approach requires a causal estimate of the impact of Medicaid on consumption, which cannot be estimated in the CEX data.[15] Second, the data come from a national sample of low-income individuals, not the Oregon study data.

In principle, it is straightforward to directly estimate the correlation between the marginal utility of consumption and out-of-pocket medical spending for uninsured individuals in the CEX data.

fact that non-medical consumption for the uninsured is presumably lowered due to out-of-pocket medical costs which are 0 for the insured, we assume that average non-medical consumption for the insured is $\bar{c} + (\bar{x})/n$ (see equation (24)) where $\bar{x}$ denotes average out-of-pocket spending for the uninsured.

[15] For the pure-insurance term of the consumption-based optimization approach, we need to evaluate the covariance term of equation (16) only for $q = 0$ because we know that the covariance term is zero for $q = 1$, given our baseline assumption that the insured face no consumption risk from medical expenditures. Hence, we do not need a causal estimate of the impact of Medicaid on consumption.

We wish to estimate equation (16). For $q = 0$, this reduces to

$$Cov\left(\frac{c(0;\theta)^{-\sigma}}{E\left[c(0;\theta)^{-\sigma}\right]}, x(0, m(0;\theta))\right),$$

where c and x are observed non-medical consumption and out-of-pocket medical spending for the uninsured in the CEX. We impose the same consumption floor as in the consumption proxy approach.

In practice, we face an additional challenge that the raw data show a negative covariance between the marginal utility of consumption and out-of-pocket spending among the uninsured. This is not an idiosyncratic feature of the CEX; we also estimate a negative covariance in the Panel Study of Income Dynamics (PSID). The negative covariance remains even after controlling for income and assets, and we suspect that the covariance term is biased from measurement error that induces a negative correlation between $c(0;\theta)^{-\sigma}$ and $x(0;\theta)$.

We therefore implement a measurement-error correction that allows for potentially nonclassical measurement error in out-of-pocket medical spending. We do so by exploiting a key implication of our model: the covariance between out-of-pocket medical spending and the marginal utility of consumption should be zero for the insured $(q = 1)$ because they have no out-of-pocket medical spending. Under the assumption that measurement error in out-of-pocket medical spending is the same for the insured and uninsured, we use the estimated covariance term for the insured to infer the impact of measurement error on the covariance term for the uninsured. Appendix A.5.2 provides more detail on our approach.

4 Results

4.1 Baseline results

4.1.1 Utility-free estimates: Medicaid costs and transfers

Without any assumptions about the utility function, the experimental estimates deliver several key objects. The gross cost of Medicaid (G) equals total medical spending for treatment compliers $(q = 1)$, since treatment compliers have no out-of-pocket spending (see equation (21)). Table 2 indicates that G is \$3,600 per recipient year. This is broadly consistent with external estimates of annual per-recipient spending in the Medicaid program in Oregon (Wallace et al. (2008)[56]).

The net cost of Medicaid (C) equals the average increase in medical spending due to Medicaid plus the average decrease in out-of-pocket spending due to Medicaid (see equation (22)). Table 2 shows the impact of Medicaid on medical spending is \$879, and on out-of-pocket spending is -\$569. Hence, $C = \$1,448$. The monetary transfer from Medicaid to external parties, N, is the difference between G and C (see equation (23)), or \$2,152 . Thus, about 60 cents of every dollar of government spending on Medicaid is a transfer to external parties $(N/G \approx 0.6)$.

Finally, the optimization approach allows us to estimate the value of the transfer component of Medicaid to recipients using only the estimates of the impact of Medicaid on m and p (see equation (14)). The change in the out-of-pocket price for medical care due to insurance $(p(0) - p(1))$ is 0.21. Using linear approximation (Assumption 4) and the estimates of $E[m(0,\theta)]$ and $E[m(1,\theta)]$ of $\$2,721$ and $\$3,600$ respectively (see Table 2), we calculate a transfer term of \$661. Without the linear approximation, we can derive lower and upper bounds for the transfer term of \$569 and \$752, respectively (see equation (15)).

4.1.2 Complete-information approach

As shown in equation (4), the complete-information approach requires us to estimate mean health outcomes and the distribution of consumption for control compliers $(q = 0)$ and for treatment compliers $(q = 1)$. Table 2 shows the estimates for mean health outcomes while Figure 1 shows the estimated distribution of consumption at $q = 0$ and $q = 1$. The complete-information approach further requires that we calibrate the marginal rate of substitution of health for consumption (ϕ) and a coefficient of relative risk aversion (σ). As discussed, our baseline specification assumes $\phi = \$5,000$ and $\sigma = 3$.

This implementation of the complete-information approach yields an estimate of $\gamma(1) = \$1,675$. In other words, a Medicaid recipient would be indifferent between giving up Medicaid and giving up $1,675 in consumption. The complete-information approach lends itself to decomposing $\gamma(1)$ into the component operating through health (γ_h) and the component operating through consumption (γ_C). We define γ_C as:

$$E\left[\frac{c(0;\theta)^{1-\sigma}}{1-\sigma}\right] = E\left[\frac{(c(1;\theta)-\gamma_C)^{1-\sigma}}{1-\sigma}\right], \tag{25}$$

and estimate $\gamma_C = \$1,381$. We then infer the value of Medicaid to recipients operating through health as $\gamma_h = \gamma(1) - \gamma_C = \$294$.[16] In other words, about 80 percent of the recipient willingness to pay for Medicaid comes through its impact on consumption as opposed to health.

Decomposition of $\gamma(1)$ into a transfer term and a pure-insurance term requires estimates of heterogeneity in the return to medical spending, $\frac{d\tilde{h}}{dm}$ (see equations (6) and (7)). As mentioned above, we do not have statistical power to estimate heterogeneity in $\frac{d\tilde{h}}{dm}$. However, because the estimates of $\frac{d\tilde{h}}{dm}$ are needed only for the decomposition of the health component γ_h, we can still find the transfer term of the consumption component γ_C.[17] By setting the right hand side of equation (6) to zero, we obtain an estimate of the consumption component of the transfer term of $569. Thus, the lower bound for the entire transfer term is $569. By assuming that the entire health component ($\gamma_h = \$294$) is part of transfer term, we obtain an upper bound for the transfer term of $863 (=$569+$294). The resulting bounds on the pure-insurance component are $812 and

[16]Because of the curvature of the utility function, the order of operations naturally matters. If we instead directly estimate γ_h and infer γ_C from $\gamma(1) - \gamma_h$, we estimate $\gamma_C = \$1,059$ and $\gamma_h = \$615$.

[17]Appendix A.3 provides implementation details of how we decompose γ_C into a transfer component and a pure-insurance component. The pure-insurance component operating through consumption smoothing is broadly similar to the approach taken by Feldstein and Gruber (1995)[24] to estimate the consumption-smoothing value of catastrophic health insurance, and Finkelstein and McKnight (2008)[27] to estimate the consumption-smoothing value of the introduction of Medicare.

\$1,106. This suggests that roughly a third to a half of the value of Medicaid comes from its transfer component, with the remainder coming from Medicaid's ability to move resources across states of the world.

4.1.3 Consumption-based optimization approach

We estimate the transfer component and pure-insurance component separately, and combine them for our estimate of $\gamma(1)$. Estimation of the transfer component is straightforward, and, as described above, produced an estimate of \$661. Estimation of the "pure-insurance" component, however, is more complicated. We undertake two approaches; for both, we assume $\sigma = 3$.

Consumption-based optimization approach with consumption proxy. We estimate the pure-insurance value at $q = 0$ using equation (16) on the Oregon sample. This requires an estimate of the joint distribution of consumption and out-of-pocket spending for control compliers (see footnote 12). The distribution of c for $q = 0$ was shown in Figure 1, and the joint distribution of consumption and out-of-pocket spending follows from computing out-of-pocket spending as in equation (24). At $q = 1$, the pure-insurance value of Medicaid is zero because the marginal utility of consumption is constant. Following the linear approximation in Assumption 4, the total pure-insurance component is therefore one-half of what we estimate at $q = 0$, or \$760. Adding this to the previously estimated transfer component implies $\gamma(1) = \$1,421$.

Consumption-based optimization approach with CEX consumption measure. We also estimate the pure-insurance value at $q = 0$ using low-income individuals in the CEX. As explained in detail in Appendix A.5 and shown in Appendix Table 2, we use the difference in the observed covariance term for the uninsured and the observed covariance term for the insured to estimate the measurement-error corrected covariance term for the uninsured. The resulting measurement-error corrected covariance between the marginal utility of consumption and out-of-pocket spending at $q = 0$ is \$265 for our baseline measure of consumption. As before, the assumption that Medicaid provides full insurance implies that the pure-insurance value of Medicaid is 0 at the margin at $q = 1$. The linear approximation over $q = 1$ and $q = 0$ yields a pure-insurance value of 133. Adding this to our previously estimated transfer component implies $\gamma(1) = \$793$.

4.2 Summary and Sensitivity

The first row of Table 3 summarizes our estimates of recipient willingness to pay for Medicaid $\gamma(1)$. The estimates range from $\$1,675$ (standard error = \$60) in the complete-information approach to $\$1,421$ (standard error = \$180) in the consumption-based optimization approach using a consumption proxy, to \$793 (standard error = \$417) in the consumption-based optimization approach using the CEX consumption measure. The next two rows summarize the decomposition of $\gamma(1)$ into a transfer and a pure-insurance component. The results suggest the transfer component represents a large share of $\gamma(1)$. Under the optimization approach, the transfer component contributes between one-half and four-fifths of total willingness to pay; the bounds in the complete-information approach suggest the transfer component accounts for at least a third and as much as half of $\gamma(1)$.

Panel B provides some benchmarks. The first row shows that the net cost of providing Medicaid to recipients is only 40% of government spending on Medicaid; the majority of government spending on Medicaid goes to external parties who, in the absence of Medicaid, would have given the recipients medical care without being fully paid. The second row compares recipient willingness to pay to net cost ($C = \$1,148$). It shows that whether or not recipient willingness to pay exceeds net costs depends on the approach - with $\gamma(1)/C$ ranging from 0.55 to 1.16. A finding of $\gamma(1)$ above C implies that the insurance value of Medicaid to recipients, I, exceeds the moral hazard costs of Medicaid, $G - N - T$, while $\gamma(1)$ below C implies the converse.[18] The final row of panel B shows that the moral hazard of Medicaid is substantial across all approaches.

Naturally, all of our quantitative results are sensitive to the framework used and to our specific implementation assumptions. We explored sensitivity to a variety of alternative assumptions including: the assumed level of risk aversion, the assumed consumption floor, the measurement of

[18]By definition, $\gamma(1) = T + I$ and $C = G - N$. Therefore a comparison of I to $G - N - T$ is equivalent to a comparison of $\gamma(1)$ to C.

out-of-pocket spending for those on Medicaid, the assumed amount of within-family risk smoothing, and alternative interpolations in the optimization approach than our linear baseline. We also explored sensitivity to alternative ways of valuing health improvements and alternative health measures. As Table 1 indicated, these will affect certain estimates and not others.

Appendix B describes our sensitivity analyses and results. Across specifications, recipient willingness to pay is roughly of the same order of magnitude as net costs, the transfer value to recipients is always substantial but the estimates of the pure-insurance value are more sensitive. For the complete-information approach, the biggest impact on the estimates comes from assuming $\sigma = 5$, which raises our estimate of $\gamma(1)/C$ from 1.2 to 2.8. The next biggest effect comes from replacing our baseline calibration of a marginal rate of substitution of health for consumption of \$5,000 by a value of \$40,000, which would result if willingness to pay for health scales linearly with consumption. Under the consumption-based optimization approach using the consumption proxy, the biggest change comes from assuming that the shock is borne entirely by the individual. This more than doubles our estimate of $\gamma(1)/C$ from 1.0 to 2.2. The consumption-based optimization approach using the CEX consumption measure is more stable. The biggest impact comes from assuming $\sigma = 5$; this raises $\gamma(1)/C$ from 0.55 to 0.60.

4.3 Discussion

External parties. A striking finding is that a major beneficiary of Medicaid expansions are non-recipients, who receive 60 percent of each dollar of government Medicaid spending. An open and important question concerns the identity of these "non-recipients." The provision of uncompensated care by hospitals is a natural starting point. Recent evidence indicates that hospital visits by the uninsured are associated with very large unpaid bills (Dobkin et al. (2018)[21]) and that increases in Medicaid coverage lead to large reductions in uncompensated care by hospitals (Garthwaite, Gross, and Notowidigdo (2018)[32]).

The ultimate economic incidence of the transfers to external parties is more complicated. While some of the incidence may fall on the direct recipients of the monetary transfers, other parties including the privately insured, the recipients themselves (for example, if reductions in unpaid medical debt provide benefits to recipients), and the public sector budget may bear some of the incidence.

Recipient willingness to pay if (counterfactually) the uninsured had no implicit insurance. We assess how much higher recipient willingness to pay for Medicaid would be if (counterfactually) the low-income uninsured had no implicit insurance. To do so, we extrapolate (grossly) out of sample from the observed demand for medical care at $p = 0$ (for treatment compliers) and at $p = 0.21$ (for control compliers) to the demand for medical care at $p = 1$ (i.e., if the uninsured had to pay the full cost of their medical care). We do this by assuming that the demand for medical care is log-linear in p.[19] This out-of-sample exercise suggests that, if the low-income uninsured had to pay all of their medical costs, recipient willingness to pay for Medicaid would increase to $\$2,749$ under the complete-information approach (compared to our baseline estimate of $1,675$) and to $\$3,875$ for the consumption-based optimization approach (compared to $\$1,421$ for our baseline estimate in Table 3).

Recipient willingness to pay relative to Medicaid cost. As noted in the Introduction, the Congressional Budget Office currently uses G for the value of Medicaid for recipients (Congressional Budget Office (2012)[48]). However, a priori, $\gamma(1)$ may be less than or greater than G. If rational individuals have access to a well-functioning insurance market and choose not to purchase insurance, $\gamma(1)$ will be less than G. If market failures such as adverse selection (e.g., knowledge of θ when choosing insurance) result in private insurance not being available at actuarially fair prices, $\gamma(1)$ could exceed G, although it might not if moral hazard costs and crowd-out of implicit insurance (i.e., N) sufficiently reduce $\gamma(1)$. Ultimately these are empirical questions.

Across the different approaches, we consistently estimate that $\gamma(1)$ is less than G, with our estimates of $\gamma(1)/G$ ranging between \$0.2 and \$0.5. This implies that Medicaid recipients would

[19] Once we have an estimate of the (counterfactual) distribution of m at $p = 1$, this straightforwardly implies counterfactual distributions of x and of c (in our consumption-proxy based approach). For the complete-information approach we also need a counterfactual estimate for the mean of h, which we get by simple linear extrapolation.

rather give up Medicaid than pay the government's costs of providing Medicaid; likewise, an uninsured person would choose the status quo over giving up G in consumption to obtain Medicaid. This contrasts with the current approach used by the Congressional Budget Office to value Medicaid at government cost.

However, since the gross costs of Medicaid (G) greatly exceed its *net* costs ($C = G - N$), is is also instructive to compare $\gamma(1)$ to C. We think of this as a useful thought exercise even though it is not clear that there is a corresponding practical implementation option of delivering Medicaid without the transfer to external parties. Of course, if the government is itself a major recipient of the transfers to "external parties" (Hadley et al. (2008)[34]) our net cost estimate C may approximate the "true" cost of Medicaid to the public sector.

It is theoretically ambiguous whether $\gamma(1)$ will be higher or lower than C. Recipient willingness to pay for Medicaid may be higher than its net cost due to its insurance value, or it may be lower because of moral hazard effects. The results indicate that, depending on the approach, recipient willingness to pay for Medicaid relative to its net costs (i.e., $\gamma(1)/C$) varies from about 0.5 to 1.2.

Recipient vs. societal willingness to pay. The fact that our population has low levels of consumption (due to low levels of income and/or liquidity constraints) implies that they have a high marginal utility of consumption, which contributes to a low willingness to give up consumption for other goods. As we emphasized at the outset, *societal* willingness to pay may be considerably higher, given the redistributive nature of Medicaid. We can derive a societal willingness to pay for Medicaid by multiplying $\gamma(1)$ by the relevant social welfare weight.[20]

Consider, for example, a utilitarian social welfare function over individual utilities. Social willingness to pay is therefore recipient willingness to pay multiplied by the ratio of the marginal utility of consumption of the recipient to the marginal utility of consumption of the average person in the population. A rough calculation from the Consumer Expenditure Survey suggests that the

[20]Societal willingness to pay may also be higher than individual willingness to pay for two other reasons not captured in our analysis. First, Medicaid may provide insurance value to those not currently eligible for Medicaid, but who would become eligible if they experienced a sufficiently large negative shock. Second, government provision of insurance may reduce inefficiencies stemming from the Samaritan's dilemma (Coate (1995)[14]). Both channels are beyond the scope of our paper.

median consumption in the recipient population in the Oregon Health Insurance Experiment is about 40 percent of the median consumption level of the general population. Given our assumption of CRRA individual utility with a coefficient of relative risk aversion of $\sigma = 3$ (i.e., a marginal utility of consumption of $\frac{1}{c^3}$), this would suggest a societal willingness to pay for Medicaid that is nearly 20 times recipient willingness to pay; even with log utility, societal willingness to pay would be 2.5 times recipient willingness to pay.

An alternative approach that does not require assuming a specific social welfare function would be to compare recipient willingness to pay per dollar of government expenditure to their willingness to pay for alternative redistributional instruments, such as a tax cut (Hendren (2016)[35], Hendren (2017)[36]). This asks whether redistributing through Medicaid is a more or less costly way to transfer resources to a low-income population than other transfer programs. To make this comparison, one can compare the marginal value of public funds (MVPF) of Medicaid spending to the MVPF other policies such as the Earned Income Tax Credit (EITC). For comparison, Hendren (2016)[35] estimates an MVPF of about \$0.9 for the EITC; the recipients would be willing to pay roughly \$0.9 for every dollar of government spending on the EITC.

Whether Medicaid's MVPF compares favorably to the EITC depends critically on the ultimate economic incidence of the transfers to external parties ($N \approx 0.6G$). If the government bears the incidence of uncompensated care payments, then the cost to the government of providing Medicaid would be C so that the MVPF would be γ/C, which ranges from 0.5 to 1.2. If the low-income individuals bear the ultimate incidence of the transfers – as would be the case if reductions in uncompensated care costs for the newly insured allowed medical providers to provide better care to the remaining low-income uninsured – then the relevant comparison of the 0.9 estimate for the EITC is to $(\gamma + 0.6G)/G$. This value ranges from 0.8 to 1.1. Lastly, if the ultimate incidence of the transfers is on the high end of the income distribution – such as hospital owners or the privately insured – then Hendren (2017)[36] shows one can down-weight these gains by the marginal cost of moving \$1 from the top to the bottom of the income distribution through modifications to the tax schedule, which yields an estimated weight of 0.5. In this case, the relevant EITC comparison could be to $((\gamma+0.3G)/G$ or 0.5 to 0.8. Thus, if affluent populations are the ultimate beneficiaries of reductions in uncompensated care, it suggests the MVPF or "bang for the buck" for Medicaid spending is lower than the EITC.

4.4 Tradeoffs across alternative approaches

We highlight some of the tradeoffs and limitations across the various approaches; we also highlight which limitations could be surmounted with better data and which are fundamental limitations of each approach.

First, as noted in Section 3.3, we rely on stated preferences to translate our measured impacts of Medicaid on health into quality-adjusted life years (QALYs), which we then value using an estimate of the marginal rate of substitution (MRS) of health for consumption among a low-income population. Reasonable people may well have serious concerns about either the reliability of QALYs or the assumptions we make to translate a VSLY estimate into a MRS for our low-income population. In other settings, direct estimates of the mortality impact of Medicaid would allow the researcher to avoid QALYs, but would still require an assumption about the MRS for a low-income population. As a result, readers wishing to avoid estimates of the VSLY or its translation into an MRS may prefer the consumption-based optimization approach which does not require such assumptions.

Second, with better consumption data for the Oregon study population, one could avoid using a consumption proxy in both the complete-information approach and the consumption-proxy variant of the consumption-based optimization approach. Willingness to pay estimates using our consumption proxy may be biased upward since the proxy assumes the uninsured have no means of smoothing consumption through savings or borrowing.

Third, our estimates from the optimization approaches may be biased (in either direction) due to imperfect measurement of prices. Our estimate of $p(0)$ is based on the average price for the uninsured, while the relevant price for welfare analysis is the marginal price of medical care for the uninsured. The marginal price may be higher than the average price if the uninsured tend to avoid treatments for which they would have to pay a higher out-of-pocket price. Or, it might be lower than the average price if the uninsured effectively face no out-of-pocket costs above a certain level of expenditures (Mahoney (2015)[40]). A downward bias in our estimate of $p(0)$ reduces the estimate of $\gamma(1)$ (see equation 12) and creates an upward bias in the effect on external parties, N. An upward bias in $p(0)$ has the opposite effect.

Fourth, the linear interpolation between $\frac{d\gamma(0)}{dq}$ and $\frac{d\gamma(1)}{dq}$ used in the optimization approaches may downward bias our estimates of $\gamma(1)$ since it does not allow for the possibility that some of the benefit of health insurance may operate via an "access motive" in which additional income (or liquidity) allows for discontinuous or lumpy changes in health care consumption (Nyman (1999a,b)[42, 43]). This limitation cannot be addressed with better data (short of observing a program that would give individuals partial Medicaid coverage).[21] By contrast, the complete-information approach would accurately capture the value stemming from the liquidity Medicaid provides.

We also highlight some general tradeoffs between the optimization and complete-information approaches. Since the complete-information approach requires specifying all arguments of the utility function while the optimization approaches do not, omission of any utility-relevant outcomes that are affected by Medicaid may bias the complete-information estimate of $\gamma(1)$ (in either direction). On the other hand, the optimization approaches assume that individuals have the ability and information to maximize their utility. If this assumption is violated, we will mismeasure how much they value the relaxation of the budget constraint provided by Medicaid, which can bias our estimate of $\gamma(1)$ in either direction.

Fundamentally, even with ideal data, all of the approaches developed here require assumptions about the shape of the utility function. Other methods that substitute alternative assumptions can provide a useful complement to the approaches developed here. For example, Krueger and

[21] Consider an extreme example in which there is a single expensive medical procedure that individuals may undergo in the event of a health shock and in which individuals are sufficiently liquidity constrained that they will undertake this procedure only if $q \geq 0.4$. As a result, $\frac{d\gamma}{dq}$ would be zero until $q = 0.4$, jump up at $q = 0.4$ and decline thereafter. The linear approximation would not capture the relatively large values of $\frac{d\gamma}{dq}$ that would occur for intermediate values of q and would in this case underestimate $\gamma(1)$.

Kuziemko (2013)[38] directly survey individuals about their stated willingness to pay for hypothetical health insurance plan offerings, while Finkelstein, Hendren, and Shepard (2017)[26] estimate demand for private health insurance in a low-income population and interpreted the demand curve through the lens of revealed preference.

A final distinction between the optimization approaches and the complete-information approach that could be relevant in other settings is that the complete-information approach is better suited to do welfare analysis when there are externalities or when the social welfare function does not solely take individuals' utilities as arguments. In such cases, we could put different social weights on different components of utility (e.g., the consumption component vs. the health component) to capture externalities or paternalistic social welfare preferences. This is obviously not possible with the optimization approaches, because those don't allow for a decomposition of utility into its components.

5 Conclusion

Welfare analysis of non-market goods is important, but also challenging. As a result, the benefits from Medicaid to its recipients are often ignored in academic and public policy discourse, or based on ad-hoc approaches. In this paper, we developed, implemented, and compared alternative formal frameworks for valuing a Medicaid expansion for low-income, uninsured adults that occurred by random assignment in Oregon.

Our analysis uncovers that Medicaid is best conceived of as having two distinct parts: a subsidized health insurance product for low-income individuals and a transfer to external parties who would otherwise subsidize medical care for the low-income uninsured. We estimate that 60 cents of every dollar of government Medicaid spending is a transfer to these external parties. This suggests the importance of future work studying their immediate and ultimate economic incidence.

A priori, recipient willingness to pay for Medicaid could be higher or lower than the net (of transfer to external parties) cost of Medicaid. Our results here are sensitive to the framework used, with estimates of recipient willingness to pay per dollar of net cost ranging from 0.5 to 1.2. Across approaches, recipient willingness to pay coming from Medicaid transfer of resources (since the insurance is heavily subsidized) is relatively stable around 0.5 dollars per dollar of net cost, whereas estimates of recipient willingness to pay for the pure (budget-neutral) insurance component vary considerably.

Our empirical findings are naturally specific to our setting. In particular, as noted in Finkelstein et al. (2012)[28], the impact of Medicaid may well differ when it is mandatory rather than voluntary, when it is expanded to cover a larger number of individuals, or when it is provided over a longer time horizon. The value of Medicaid may also differ for other Medicaid populations than the low-income adult population studied here, such as children, the disabled, or the elderly, for whom there is also a large empirical literature on Medicaid's effects (see Buchmueller et al. (2015)[8] for a recent review). However, the approaches we have developed can be applied to studying the value of Medicaid in other contexts.

Our approach can also be adapted to study the welfare impact of other social insurance programs. For example, for disability insurance, an existing literature uses approaches analogous to our "complete-information approach" for welfare analysis (e.g., Autor et al. (2017)[3]). Our frameworks clarify the role of the modeling assumptions in these welfare analyses and provide potential pathways to use the optimization-based approaches to relax some of these assumptions. Likewise, our frameworks could be applied to Medicare, where there is a large empirical literature examining the impacts of Medicare on welfare-relevant outcomes such as health care use, health, and out-of-pocket medical expenditures (e.g., Card et al. (2008, 2009)[9, 10], Barcellos and Jacobson (2015)[7]).

Our paper illustrates the possibilities – but also the challenges – in doing welfare analysis even with a rich set of causal program effects. Behavioral responses are not prices and do not reveal willingness to pay without additional assumptions. We provide a range of potential pathways to welfare estimates under various assumptions, and offer a range of estimates that analysts can consider. These approaches advance beyond common defaults of zero valuation or valuation at government cost. We hope the flexibility offered by these approaches provides guidance to future research examining the welfare impact of the public provision of other non-market goods.

References

[1] Joshua D. Angrist and Jörn-Steffen Pischke. Mostly harmless econometrics: An empiricist's companion. *Princeton University Press*, 2009.

[2] Kenneth J. Arrow. Uncertainty and the welfare economics of medical care. *American Economic Review*, 53(5):941–973, 1963.

[3] David Autor, Andreas Ravndal Kostol, Magne Mogstad, and Bradley Setzler. Disability benefits, consumption insurance, and household labor supply. NBER Working Paper No. 23466, 2017.

[4] Katherine Baicker, Amy Finkelstein, Jae Song, and Sarah Taubman. The impact of Medicaid on labor force activity and program participation: Evidence from the Oregon Health Insurance Experiment. *American Economic Review: Papers and Proceedings*, 104(5):322–328, 2014.

[5] Katherine Baicker, Sendhil Mullainathan, and Joshua Schwartzstein. Behavioral hazard in health insurance. *Quarterly Journal of Economics*, 130(5):1623–1667, 2015.

[6] Katherine Baicker, Sarah Taubman, Heidi Allen, Mira Bernstein, Jonathan Gruber, Joseph Newhouse, Eric Schneider, Bill Wright, Alan Zaslavsky, Amy Finkelstein, and the Oregon Health Study Group. The Oregon experiment – effects of Medicaid on clinical outcomes. *New England Journal of Medicine*, 368:1713–1722, 2013.

[7] Silvia Helena Barcellos and Mireille Jacobson. The effects of Medicare on medical expenditure risk and financial strain. *American Economic Journal: Economic Policy*, 7(4):41–70, 2015.

[8] Thomas Buchmueller, John Ham, and Lara Shore-Sheppard. Medicaid. In Robert A. Moffitt, editor, *Means-tested transfer programs in the United States, II*. University of Chicago Press, in progress.

[9] David Card, Carlos Dobkin, and Nicole Maestas. The impact of nearly universal insurance coverage on health care utilization: Evidence from Medicare. *American Economic Review*, 98(5):2242–2258, 2008.

[10] David Card, Carlos Dobkin, and Nicole Maestas. Does Medicare save lives? *Quarterly Journal of Economics*, 124(2):597–636, 2009.

[11] James H. Cardon and Igal Hendel. Asymmetric information in health insurance: Evidence from the National Medical Expenditure Survey. *RAND Journal of Economics*, 32(3):408–427, 2001.

[12] Amitabh Chandra, Anupam B. Jena, and Jonathan S. Skinner. The pragmatist's guide to comparative effectiveness research. *Journal of Economic Perspectives*, 25(2):27–46, 2011.

[13] Raj Chetty. Sufficient statistics for welfare analysis: A bridge between structural and reduced-form methods. *Annual Review of Economics*, 1(1):451–488, 2009.

[14] Stephen Coate. Altruism, the samaritan's dilemma, and government transfer policy. *American Economic Review*, 85(1):46–57, 1995.

[15] Teresa A. Coughlin, John Holahan, Kyle Caswell, and Megan McGrath. Uncompensated care for uninsured in 2013. Technical report, Kaiser Commission on Medicaid and the Uninsured, May 2014.

[16] Maureen Cropper, James K. Hammitt, and Lisa A. Robinson. Valuing mortality risk reductions: Progress and challenges. *Annual Review of Resource Economics*, 3:313–336, 2011.

[17] Janet Currie and Firouz Gahvari. Transfers in cash and in-kind: Theory meets the data. *Journal of Economic Literature*, 46(2):333–383, 2008.

[18] David M. Cutler. Your money or your life: Strong medicine for America's health care system. *New York: Oxford University Press*, 2004.

[19] David M. Cutler, Robert S. Huckman, and Jonathan T. Kolstad. Input constraints and the efficiency of entry: Lessons from cardiac surgery. *American Economic Journal: Economic Policy*, 2(1):51–76, 2010.

[20] Laura Dague. The effect of Medicaid premiums on enrollment: A regression discontinuity approach. *Journal of Health Economics*, 37:1–12, 2014.

[21] Carlos Dobkin, Amy Finkelstein, Raymond Kluender, and Matthew J. Notowidigdo. The economic consequences of hospital admissions. *American Economic Review*, 108(2):308–52, 2018.

[22] Isaac Ehrlich and Gary S. Becker. Market insurance, self-insurance, and self-protection. *Journal of Political Economy*, 80(4):623–648, 1972.

[23] Liran Einav, Amy Finkelstein, and Jonathan Levin. Beyond testing: Empirical models of insurance markets. *Annual Review of Economics*, 2(1):311–336, 2010.

[24] Martin Feldstein and Jonathan Gruber. A major risk approach to health insurance reform. In James M. Poterba, editor, *Tax Policy and the Economy, Volume 9*, pages 103–130. MIT Press, 1995.

[25] Amy Finkelstein, Nathaniel Hendren, and Erzo F.P. Luttmer. The value of Medicaid: Interpreting results from the Oregon Health Insurance Experiment. NBER Working Paper No. 21308, 2015.

[26] Amy Finkelstein, Nathaniel Hendren, and Mark Shepard. Subsidizing health insurance for low-income adults: Evidence from Massachusetts. NBER Working Paper No. 23668, 2017.

[27] Amy Finkelstein and Robin McKnight. What did Medicare do? The initial impact of Medicare on mortality and out of pocket medical spending. *Journal of Public Economics*, 92(7):1644–1668, 2008.

[28] Amy Finkelstein, Sarah Taubman, Bill Wright, Mira Bernstein, Jonathan Gruber, Joseph P. Newhouse, Heidi Allen, and Katherine Baicker. The Oregon Health Insurance Experiment: Evidence from the first year. *Quarterly Journal of Economics*, 127(3):1057–1106, 2012.

[29] Amy N. Finkelstein, Sarah L. Taubman, Heidi L. Allen, Bill J. Wright, and Katherine Baicker. Effect of Medicaid coverage on ED use - Further evidence from Oregon's experiment. *New England Journal of Medicine*, 375:505–1507, 2016.

[30] Trevor S. Gallen. Using participant behavior to measure the value of social programs: The case of Medicaid. Working paper, Purdue University, 2015.

[31] Jorge Luis Garcia, James J. Heckman, Duncan Ermini Leaf, and Maria Jose Prados. Quantifying the life-cycle benefits of a prototypical early childhood program. NBER Working Paper No. 23479, 2017.

[32] Craig Garthwaite, Tal Gross, and Matthew J. Notowidigdo. Hospitals as insurers of last resort. *American Economic Journal: Applied Economics*, 10(1):1–31, 2018.

[33] Peter Gottschalk and Timothy M. Smeeding. Cross-national comparisons of earnings and income inequality. *Journal of Economic Literature*, 35(2):633–687, 1997.

[34] Jack Hadley, John Holahan, Teresa Coughlin, and Dawn Miller. Covering the uninsured in 2008: Current costs, sources of payment, and incremental costs. *Health Affairs*, 27(5):w399–w415, 2008.

[35] Nathaniel Hendren. The policy elasticity. *Tax Policy and the Economy*, 30, 2016.

[36] Nathaniel Hendren. Efficient welfare weights. NBER Working Paper No. 20351, 2017.

[37] Michael Keane and Robert Moffitt. A structural model of multiple welfare program participation and labor supply. *International Economic Review*, 39(3):553–589, 1998.

[38] Alan Krueger and Ilyana Kuziemko. The demand for health insurance among uninsured Americans: Results of a survey experiment and implications for policy. *Journal of Health Economics*, 32(5):780–793, 2013.

[39] Darius Lakdawalla, Anup Malani, and Julian Reif. The insurance value of medical innovation. *Journal of Public Economics*, 145:94–102, 2017.

[40] Neale Mahoney. Bankruptcy as implicit health insurance. *American Economic Review*, 105(2):710–746, 2015.

[41] MEPS. MEPS HC-147 2011 full year consolidated data file. `https://meps.ahrq.gov/mepsweb/data_stats/download_data_files_detail.jsp?cboPufNumber=HC-147`, 2013.

[42] John A. Nyman. The economics of moral hazard revisited. *Journal of Health Economics*, 18(6):811–824, 1999.

[43] John A. Nyman. The value of health insurance: The access motive. *Journal of Health Economics*, 18(2):141–152, 1999.

[44] Arthur Okun. *Equality and Efficiency*. Brookings Institution Press, 1975.

[45] Emmanuel Saez and Stefanie Stantcheva. Generalized social welfare weights for optimal tax theory. *American Economic Review*, 106(1):24–45, 2016.

[46] Paul A. Samuelson. The pure theory of public expenditure. *Review of Economics and Statistics*, 36(4):387–389, 1954.

[47] Sarah Taubman, Heidi Allen, Bill Wright, Katherine Baicker, Amy Finkelstein, and the Oregon Health Study Group. Medicaid increases emergency-department use: Evidence from Oregon's health insurance experiment. *Science*, 343:263–268, 2014.

[48] U.S. Congressional Budget Office. The distribution of household income and federal taxes, 2008 and 2009. 2012.

[49] U.S. Department of Agriculture. The food assistance landscape: FY 2015 annual report. 2016.

[50] U.S. Department of Health and Human Services. 2015 actuarial report on the financial outlook for Medicaid. 2015.

[51] U.S. Department of Health and Human Services. FY 2015 Federal TANF & state MOE financial data. 2016.

[52] U.S. Internal Revenue Service. EITC calendar year report. 2015.

[53] U.S. Social Security Administration. Social Security Income program 2016 technical materials. February 2016.

[54] Eddy Van Doorslaer and Andrew M. Jones. Inequalities in self-reported health: Validation of a new approach to measurement. *Journal of Health Economics*, 22(1):61–87, 2003.

[55] W. Kip Viscusi. The value of risks to life and health. *Journal of Economic Literature*, 31(4):1912–1946, 1993.

[56] Neal T. Wallace, K. John McConnell, Charles A. Gallia, and Jeanene A. Smith. How effective are copayments in reducing expenditures for low-income adult Medicaid beneficiaries? Experience from the Oregon health plan. *Health Services Research*, 43(2):515–530, 2008.

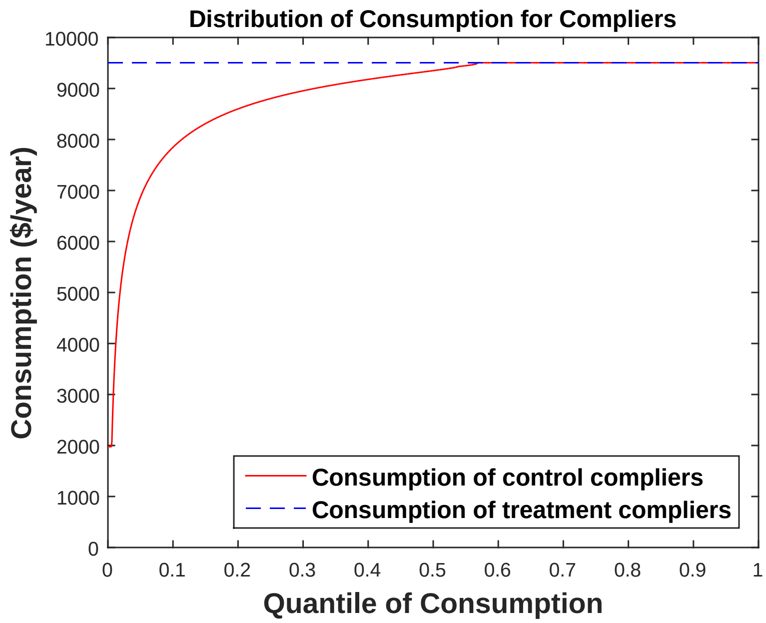

Figure 1: Consumption Distribution for Treatment and Control Compliers

Table 1: Overview of Empirical Objects

	I	II	III		
			Used for which estimates in which framework(s)		
			Complete	Optimization	
	Notation	Meaning	Info.	Cons.-based	Health-based
Panel A: Estimated objects					
(1)	$E[x(q,m(q;\theta))]$ for $q=0,1$	Mean out-of-pocket spending without and with Medicaid	C, G, N	C, G, N	C, G, N
(2)	$E[m(q;\theta)]$ for $q=0,1$	Mean medical spending without and with Medicaid	C, G, N	C, G, N, $\gamma(1)$	C, G, N, $\gamma(1)$
(3)	$E[h(q;\theta)]$ for $q=0,1$	Mean health without and with Medicaid	$\gamma(1)$	-	-
(4)	$\frac{d\tilde{h}(m;\theta)}{dm}$	Distribution (across health states) of impact of medical spending on health	-	-	$\gamma(1)$
(5)	$c(q;\theta)$ for $q=0,1$	Distribution of consumption without and with Medicaid	$\gamma(1)$	$\gamma(1)$	-
(6)	$p(q)$ for $q=0,1$	Out-of-pocket price for medical care without and with Medicaid	-	$\gamma(1)$	$\gamma(1)$
(7)	$x(q,m(q;\theta))$ for $q=0,1$	Distribution of out-of-pocket medical spending without and with Medicaid	-	$\gamma(1)$	$\gamma(1)$
Panel B: Parameters of the Utility Function					
(1)	σ	Coefficient of relative risk aversion	$\gamma(1)$	$\gamma(1)$	-
(2)	ϕ	MRS of health for consumption	$\gamma(1)$	-	$\gamma(1)$

Note: $\gamma(1)$ denotes recipient willingness to pay (out of current consumption) for Medicaid; G denotes the gross cost to the government of providing Medicaid; N denotes monetary transfers to non-recipient external parties, and $C = G - N$ denotes the net cost of Medicaid. All values are per Medicaid recipient. An empty cell ("-") in column 3 means that the required object listed in the row is not needed for the approach listed in the column.

Table 2: Summary Statistics

	I	II	III	IV
	Full Sample	Treatment Compliers (q=1)	Control Compliers (q=0)	Impact of Medicaid
Panel A: Oregon Data Demographics				
Share female	0.60	0.57	0.60	
Share age 50-64	0.34	0.36	0.35	
Share age 19-49	0.66	0.64	0.65	
Share white	0.83	0.84	0.84	
Share black	0.03	0.03	0.03	
Share Spanish / Hispanic / Latino	0.11	0.07	0.08	
Mean family size, n	2.97	2.88	2.91	
Panel B: Oregon Data Outcomes				
12-month medical spending, m				
Mean medical spending ($), E[$m$]	2991	3600	2721	879
Fraction with positive medical spending, E[m>0]	0.74	0.79	0.72	0.07
12-month out-of-pocket spending, x				
Mean out-of-pocket spending ($), E[$x$]	470	0	569	-569
Fraction with positive out-of-pocket spending, E[x>0]	0.38	0	0.56	-0.56
Health expressed in QALYs, E[h]	0.77	0.78	0.74	0.05
Share in poor health (QALY=0.401)	0.11	0.10	0.17	-0.07
Share in fair health (QALY=0.707)	0.30	0.29	0.36	-0.07
Share in good health (QALY=0.841)	0.36	0.38	0.28	0.10
Share in very good health (QALY=0.931)	0.17	0.18	0.15	0.03
Share in excellent health (QALY=0.983)	0.05	0.05	0.04	0.02

Notes: This table reports data from a mail survey of participants in the Oregon Health Insurance Experiment (N=15,498). Columns II and III report the implied means for treatment and control compliers in the Oregon Health Insurance Experiment and column IV reports the estimated impact of Medicaid (i.e., the difference between Columns III and II). Since it cannot be directly observed whether any particular observation is a complier, the results in columns II and III are estimated using the IV techniques described in more detail in Appendix A2.1., as are the results in column IV. The Oregon health insurance lottery is used as an instrument for Medicaid coverage.

Table 3: Willingness to Pay for Medicaid by Recipients

	I	II	III
		Optimization Approaches	
	Complete-Information Approach	Consumption-Based (Consumption Proxy)	Consumption-Based (CEX Consumption Measure)
A. Recipient WTP for Medicaid, $\gamma(1)$	1675	1421	793
(standard error)	(60)	(180)	(417)
Transfer component, *T*	569-863	661	661
Pure-insurance component, *I*	812-1106	760	133
B. Benchmarks			
Net costs as fraction of gross cost, *C/G*	0.40	0.40	0.40
Recipient WTP as fraction of net cost, $\gamma(1)/C$	1.16	0.98	0.55
Moral hazard cost, *G-T-N*	585-879	787	787

Notes: Estimates of WTP and moral hazard costs are expressed in dollars per year per Medicaid recipient. Standard errors are bootstrapped with 500 repetitions.