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

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

February 2015

Abstract

We develop and implement a set of frameworks for valuing Medicaid coverage for recipients and apply them to welfare analysis of the Oregon Health Insurance Experiment, a Medicaid expansion that occurred via random assignment. Our baseline estimates of the welfare benefit to recipients from Medicaid per dollar of government spending range from about $0.2 to $0.4, depending on the framework, with a relatively robust lower bound of $0.2. At least two-fifths - and as much as four-fifths - of the value of Medicaid comes from a pure transfer component, as opposed to its ability to move resources across states of the world. In addition, we estimate that Medicaid generates a substantial transfer to non-recipients of about $0.6 per dollar of government spending.

1 Introduction

Medicaid is the largest means-tested program in the United States. In 2011, public expenditures on Medicaid were over $425 billion, compared to $80 billion for food stamps (SNAP), $50 billion for the Earned Income Tax Credit (EITC), $50 billion for Supplemental Security Income (SSI), and $33 billion for cash welfare (TANF).† Moreover, with the 2014 state expansions of Medicaid under the Affordable Care Act, Medicaid spending is projected to be about $70 billion higher per year, on average, over the next 10 years.‡

What are the welfare benefits of these large public expenditures? How do they compare to the cost of the program to taxpayers? How does recognition of this large in-kind transfer affect estimates of inequality and poverty?

*MIT, Harvard, and Dartmouth. We are grateful to Lizi Chen for outstanding research assistance and to Isaiah Andrews, Jonathan Gruber, Conrad Miller, and Matthew Notowidigdo 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).
†See Congressional Budget Office (2013)[46], Centers for Medicare and Medicaid Services (2012)[44], and Department of Health and Human Services (2012)[48]
‡Congressional Budget Office (2014)[47].
Such empirical welfare questions have received very little attention. Although 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, financial security, labor supply, and private health insurance coverage\(^3\) - there has been little formal attempt to translate such estimates into statements about welfare. Absent other guidance, the standard practice in both academia and public policy is to either ignore the value of Medicaid - for example, in the calculation of the poverty line, or in analysis of income inequality (Gottschalk and Smeeding (1997)[31]) - or to make fairly ad hoc assumptions. For example, the Congressional Budget Office (2012) [45] values Medicaid at the average government expenditure per recipient.

Recently, 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 were: In its first one to two years, 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.\(^4\) These results have attracted considerable attention, because of the use of random assignment and the fact that the affected population is similar to those who are newly covered by the 2014 Medicaid expansions under the Affordable Care Act. But in the absence of any formal welfare analysis, it has been left to partisans and media pundits to opine on the welfare implications of these findings.\(^5\)

Can we do better? Empirical welfare analysis is challenging when the good in question - in this case public health insurance for low-income individuals - is not traded in a well-functioning market. This precludes 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) [42]).

In this paper, we develop two main analytical frameworks for empirical welfare analysis of Medicaid coverage and apply them to the results from the Oregon Health Insurance Experiment.

---

\(^3\)References for these outcomes include, respectively Currie and Gruber (1996a,b)[17],[18], Garthwaite, Gross and Notowidigdo (2014)[29], and Cutler and Gruber (1996) [20].

\(^4\)For more detail on these results, as well as on the experiment and affected population, see Finkelstein et al., (2012)[27], Baicker et al. (2013)[6], Taubman et al., (2014)[43], and Baicker et al. (2014) [4].

Our first approach, which we refer to as the “complete-information” approach, requires complete specification of a normative utility function and estimates of the causal effect of Medicaid on the distribution of all utility-relevant arguments. A key advantage of this approach 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. Moreover, it will fail to accurately measure the value of Medicaid if not all utility-relevant arguments that Medicaid impacts are specified and analyzed. In our application, for example, we specify a utility function over non-health consumption and health, and limit our empirical analysis to estimates of the impact of Medicaid on the distribution of these outcomes. In principle, however, the approach requires estimates of the impact of Medicaid on, and the value of, any utility arguments that a creative reader or referee could deem plausibly affected by the program, including for example, future consumption, marital stability, or outcomes of the recipient’s children. This creates a potential methodological bias, as one can keep conjecturing about additional potential utility arguments until one is satisfied with the magnitude of the welfare estimates.

Our second approach, which we refer to as the “first-order condition” 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. By parameterizing the precise budget sets that individuals face with and without Medicaid coverage, and by assuming that individuals make optimal choices with respect to the resultant budget sets, we can significantly reduce the implementation requirements. In particular, it suffices to specify the marginal utility function over any single argument (because the optimizing individual’s first-order condition allows us to value - through the marginal utility of that single argument - marginal impacts of Medicaid on any other potential arguments of the utility function) and to estimate the causal impact of Medicaid only on that marginal utility function. We develop two main versions of the first-order condition approach. The “consumption first-order condition approach” values Medicaid’s marginal relaxation of the recipient’s budget constraint using its covariance with the marginal utility of consumption; insurance is valuable if it transfers resources from low to high marginal utility of consumption states of the world. The “health first-order condition approach” values marginal relaxation of the budget constraint using its covariance with the marginal utility of out-of-pocket medical spending; insurance is valuable if it transfers resources from states of the world where the marginal health returns to out-of-pocket spending are low to states where those returns are high. Importantly, to use these “local” first-order condition approaches to make inferences about non-marginal changes in an individual’s budget set (e.g., coverage by Medicaid), we require additional statistical assumptions that allow us to interpolate between local estimates of the marginal impact of program generosity; these substitute for some of the economic assumptions about the utility function in the complete-information approach.

This causal impact is required only for welfare analysis of non-marginal changes in Medicaid (i.e., discrete jumps in the price of medical care). Because of the envelope theorem, this causal impact is not required for welfare analysis of small changes in the price of medical care $t$.  

3
When implementing these approaches for welfare analysis of the Medicaid coverage provided by the Oregon Health Insurance Experiment, we use the lottery’s random selection as an instrument for Medicaid coverage in order to estimate the impact of Medicaid on the required objects. Absent a consumption survey in the Oregon context, we proxy for consumption as the difference between income and out-of-pocket medical expenditures, subject to a consumption floor; we also implement an alternative version of the consumption first-order condition approach which measures consumption directly for a non-Oregon sample in the Consumer Expenditure Survey. Our baseline health measure is self-reported health, but we also report results using alternative measures, such as mortality and depression. Finally, we estimate the impact of Medicaid on government spending, in order to provide an estimate of program costs against which to compare our estimates of welfare benefits to Medicaid recipients.

All of our estimates indicate a welfare benefit to recipients below cost. Our baseline estimates indicate a welfare benefit to recipients per dollar of government spending of about $0.4 from the complete-information approach and from the consumption first-order condition approach using a consumption proxy, and about $0.2 from the other two first-order condition approaches. The differences in welfare estimates across the approaches primarily reflects different estimates of the “pure insurance” value of Medicaid (i.e. its ability to move resources across states of the world). In all the approaches, at least two-fifths - and as much as four-fifths - of the value of Medicaid comes from a pure transfer component.

Across a variety of alternative specifications, we estimate welfare benefits to recipients per dollar of government spending ranging from about $0.2 to $0.9. We discuss below which modeling assumptions, features of the data, and parameter calibrations drive the differences across our estimates. We also explain why $0.2 is a relatively robust lower bound for the welfare benefit to recipients per dollar of government spending, independent of the utility function assumptions.

Importantly, in addition to these benefits to Medicaid recipients, we also estimate that Medicaid delivers a large net transfer of about $0.6 per dollar of government spending to external parties. This stems from our finding that those not covered by Medicaid pay only a small fraction of their own medical expenses. Other parties pay the balance of the uninsured’s medical cost in the absence of Medicaid. The immediate identity of these external parties - and, more importantly, the ultimate economic incidence of the transfers to them - represent important, but challenging, areas for further work.

How seriously should our empirical welfare estimates be taken? We leave it to the readers to make up their own minds about the credibility of the various assumptions that the alternative approaches require. One thing that seems hard to disagree with is that some attempt - or combination of attempts - allows for a more informed posterior of the value of Medicaid to recipients than the implicit default of treating the value of Medicaid at zero or simply at cost, which occurs in so much existing work. Although we focus on the specific context of the value of Medicaid in the Oregon Health Insurance Experiment, 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. More generally, the basic challenges and tradeoffs we describe may also be of use for welfare analysis of other social insurance programs in settings where individuals do not reveal their willingness to pay through ex-ante choices.

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 of that welfare analysis. The last section concludes.

2 Frameworks for welfare analysis

2.1 Complete-information approach

Individual welfare is derived from the consumption of non-medical goods and services, $c$, and from health, $h$, according to the utility function:

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

We assume health is produced according to:

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

where $m$ denotes the consumption of medical care and $\theta \in \Theta$ is an underlying state variable for the individual which includes, among other things, medical conditions and other factors affecting health and the productivity of medical spending.\footnote{Formally, we assume $\Theta$ is a measurable probability space with measure $\mu$.} 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 conduct our analysis assuming that every potential Medicaid recipient faces the same distribution of $\theta$. Conceptually, we think of our welfare analysis as conducted from behind the veil of ignorance; alternatively, from the perspective of individuals who have knowledge about their type $\theta$, our welfare estimates capture both redistribution and insurance benefits to Medicaid recipients.

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, $\theta$; this dependence is denoted by $c(q; \theta)$, $m(q; \theta)$ and $h(q; \theta) \equiv \tilde{h}(m(q; \theta); \theta)$, respectively.\footnote{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].}

It would be common to define the welfare impact of Medicaid using equivalent or compensating variation. However, such notions require assumptions about optimization and a specification of the budget set. Given the large literature questioning the optimality of healthcare choices (see,
e.g., Baicker et al., (2012) [7] for a description of some of this literature), we avoid making such assumptions at the outset. We therefore define the welfare impact for Medicaid recipients, $\gamma(q)$, as the implicit solution to:

$$E[u(c(0;\theta), h(0;\theta))] = E[u(c(q;\theta) - \gamma(q), h(q;\theta))],$$

where the expectations are taken with respect to the measure $\mu$ of possible states of the world, $\theta$. Thus, $\gamma(1)$ is 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 without Medicaid.\(^9\)

The complete-information approach follows immediately from the above setup. We estimate $\gamma(1)$ by directly implementing equation (3). This requires that we estimate the full distribution of all utility-relevant variables (consumption and health in the above model) for individuals if they were to have no Medicaid ($q = 0$) and if they were to be covered by Medicaid ($q = 1$), and it requires that we completely specify the normative utility function over all of these arguments.

### 2.2 First-order condition approaches

We can reduce the information requirements by making assumptions on other dimensions. Specifically, we make assumptions regarding how the program impacts the individual’s budget set, and about individual choice behavior. This will allow us to use the individual’s first-order condition to value marginal changes in Medicaid benefits.

We let values of $q$ between 0 and 1 denote a path, defined below, between no Medicaid and Medicaid. For marginal changes in Medicaid benefits, the first-order conditions will hold locally and provide information about $d\gamma/dq$. We will then use additional statistical assumptions to integrate these marginal welfare impacts to obtain the total (non-marginal) welfare estimate corresponding to $\gamma(1)$. We characterize two versions of the first-order condition approach, corresponding to the two arguments of the utility function in equation (1).

#### 2.2.1 Additional assumptions

We assume that individuals face an out-of-pocket spending schedule for medical spending $m$, which we denote with $x(q, m)$.\(^{10}\) Without Medicaid, the “uninsured” individual faces an expenditure schedule $x(0, m)$, which denotes the individual’s total out-of-pocket expenditure required to obtain $m$ units of medical spending. Under Medicaid, the “insured” individual faces the out-of-pocket expenditure schedule $x(1, m)$. While $q$ indicates Medicaid status, the approach allows for other forms of formal and informal insurance by not requiring that those without Medicaid pay all their medical expenses out of pocket (i.e., we do not impose that $x(0, m) = m$).

We can now precisely define the path of partial insurance programs in between “uninsured” and “insured.”

\(^9\)Note that $\gamma$ is measured in terms of consumption rather than income, and is therefore not necessarily interpretable as “willingness to pay” or “willingness to give up.”

\(^{10}\)Note that $x(q, 0)$ denotes the amount an individual pays with no utilization, i.e., the insurance premium.
Assumption 1. (Program structure) We model the Medicaid program \( q \) as affecting the individual solely through its impact on the out-of-pocket expenditure schedule \( x(q,m) \).

Importantly, this assumption rules out other ways in which Medicaid might affect \( c \) or \( h \), such as through direct effects on provider behavior. We define \( q \in [0,1] \) as indexing a linear path between the out-of-pocket expenditure schedules of the uninsured and the insured:

\[
x(q,m) = qx(1,m) + (1 - q) x(0,m) \quad \forall m, q \in [0,1].
\]

We denote consumption, medical spending, and health outcomes along this path by \( c(q;\theta) \), \( m(q;\theta) \), and \( h(q;\theta) \), with \( 0 \leq q \leq 1 \).

Next, we assume that individuals make choices to optimize utility subject to a budget constraint. This is a non-trivial 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) and where the complex nature of the decision problem may generate individually suboptimal decisions (Baicker, Mullainathan and Schwartzstein (2012)).

Specifically, we assume that individuals choose medical spending, \( m(q;\theta) \), trading off the health benefits of medical spending and the consumption cost of medical spending according to the first-order condition, subject to the budget constraint.

Assumption 2. (First-order condition and budget constraint hold) Individuals’ choices of consumption, \( c \), and medical spending, \( m \), satisfy the first-order condition:

\[
E_{\theta|m} \left[ u_c(c,h) \frac{\partial x}{\partial m} \right] = E_{\theta|m} \left[ u_h(c,h) \frac{\partial h}{\partial m} \right] \quad \forall m, q,
\]

where \( h = \tilde{h}(m(q;\theta);\theta) \). Moreover, the individual’s budget constraint holds:

\[
c(q;\theta) = y(\theta) - x(q,m(q;\theta)) \quad \forall m,q,\theta.
\]

The right-hand side of equation (5) is the expected marginal benefit of additional medical spending, \( u_h(c,h) \frac{\partial h}{\partial m} \), which equals the marginal utility of health, multiplied by the increase in health provided by additional medical spending, \( \frac{\partial h}{\partial m} \). The left-hand side of equation (5) is the expected marginal cost of medical spending in terms of forgone consumption, \( u_c(c,h) \frac{\partial x}{\partial m} \). This is the marginal utility of consumption, multiplied by the reduction of consumption associated with increased medical spending, \( \frac{\partial x}{\partial m} \).

Equation (6) imposes the budget constraint. Note that this allows income \( y(\theta) \) to potentially depend on the state of the world \( \theta \); \( y(\theta) \) could also include positive or negative state-contingent

\[\text{---}\]

11 We do not require that these variables are continuous, or that their derivatives \( \frac{\partial x}{\partial q}, \frac{\partial m}{\partial q}, \) and \( \frac{\partial h}{\partial q} \) exist for all \( q \) and \( \theta \), but we require them to be integrable with respect to the measure \( \mu \).

12 By conditioning equation (5) on \( m \) rather than \( \theta \), we allow for the possibility that individuals do not fully know \( \theta \) when they choose \( m \). Thus, the first-order conditional only needs to hold in expectation, where the expectation is taken over the distribution of \( \theta \) conditional on \( m \).
changes in assets reflecting, for example, savings.

Before we can express the first-order condition approaches for valuing Medicaid, we need to derive two intermediate expressions. First, we differentiate the budget constraint with respect to \( q \):

\[
\frac{dc}{dq} = -\frac{\partial x}{\partial q} - \frac{\partial x}{\partial m} \frac{dm}{dq} \quad \forall q, \theta. \tag{7}
\]

The total change in consumption from a marginal change in Medicaid benefits, \( \frac{dc}{dq} \), equals the impact on the budget constraint, \( -\frac{\partial x}{\partial q} \), plus the impact through the behavioral response in the choice of \( m, -\frac{\partial x}{\partial m} \frac{dm}{dq} \).

Second, we use the health production function (equation (2)) to express the marginal impact of Medicaid on health, \( \frac{dh}{dq} \), as:

\[
\frac{dh}{dq} = \frac{\partial \tilde{h}}{\partial m} \frac{dm}{dq} \quad \forall q, \theta. \tag{8}
\]

This equation follows from our assumption that Medicaid affects health only through its effect on medical spending.\(^{13}\)

### 2.2.2 Consumption first-order condition approach

For the consumption first-order condition approach, we totally differentiate equation (3) with respect to \( q \), which yields the marginal welfare impact of insurance on recipients, \( \frac{d\gamma}{dq} \), as the implicit solution to:

\[
0 = E \left[ (\frac{dc}{dq} - \frac{d\gamma}{dq}) u_c + \frac{dh}{dq} u_h \right]. \tag{9}
\]

Rearranging, we obtain:

\[
\frac{d\gamma}{dq} = \frac{1}{E[u_c]} E \left[ u_c \frac{dc}{dq} + u_h \frac{dh}{dq} \right]
\]

\[
= \frac{1}{E[u_c]} E_m \left[ E_{\theta|m} \left[ u_c \left( -\frac{\partial x}{\partial q} - \frac{\partial x}{\partial m} \frac{dm}{dq} \right) + u_h \left( \frac{\partial \tilde{h}}{\partial m} \frac{dm}{dq} \right) \right] \right]
\]

\[
= \frac{1}{E[u_c]} E_m \left[ E_{\theta|m} \left[ u_c \left( -\frac{\partial x}{\partial q} \right) + E_{\theta|m} \left[ -u_c \frac{\partial x}{\partial m} + u_h \frac{\partial \tilde{h}}{\partial m} \frac{dm}{dq} \right] \right] \right]
\]

\[
= \frac{d\gamma}{dq} = E \left[ \left( \frac{u_c}{E[u_c]} \right) \left( -\frac{\partial x}{\partial q} \right) \right]. \tag{10}
\]

where the second line follows from substituting \( \frac{dc}{dq} \) and \( \frac{dh}{dq} \) (equations (7) and (8)) and using the law of iterated expectations over \( \theta \) and \( m \).

The representation in equation (10), which we call the “consumption first-order condition ap-

\(^{13}\)If we allowed Medicaid to have a direct effect on health, there would be an additional term, \( \frac{\partial \tilde{h}}{\partial q} \).
"proach," 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, the first term between parentheses in equation (10) measures the value of money in the current state of the world relative to its average value, and the second term between parentheses measures by how much Medicaid relaxes the individual’s budget constraint in the current state of the world.\footnote{Although we derived the consumption first-order condition approach using the first-order condition, equation (10) could be derived under only an assumption of optimization using the envelope theorem. As a result, equation (10) extends to a more general model that allows individuals to be at a corner with respect to their choice of medical spending. Intuitively, an individual values the mechanical increase in consumption from Medicaid according to the marginal utility of consumption, regardless of the extent to which he or she has options to substitute this increase for increases in other goods, such as health. Because all individuals have strictly positive consumption, corner solutions with respect to consumption are not a concern.} From the consumption first-order condition’s perspective, a marginal increase in Medicaid benefits delivers greater value if it moves more resources into states of the world, \( \theta \), with a higher marginal utility of consumption (e.g., states of the world with larger medical bills, and thus lower consumption). Note that the consumption first-order condition approach requires only a partial specification of the utility function (its first derivative with respect to consumption) since, via the first-order condition, the individual is indifferent between using a marginal increase in Medicaid benefits for additional consumption or additional health (via increased medical spending).

### 2.2.3 Health first-order condition approach

We can alternatively value the impact of the program on the budget constraint, \(- \frac{\partial x}{\partial q}\), using only the marginal utility of out-of-pocket medical spending, rather than the marginal utility of consumption. To do so, we use Assumption 2 to replace the marginal utility of consumption, \( u_c \) in equation (10) with a term depending on the marginal utility of health, \( u_h \), yielding:

\[
\frac{d\gamma}{dq} = E_m \left[ \frac{u_h}{E[u_c]} \frac{d\tilde{h}}{dm} - \frac{\partial x}{\partial q} \right].
\]

We refer to equation (11) as the “health first-order condition approach.” From the health first-order condition’s perspective, the program delivers greater value if it moves more resources to states of the world with a greater expected return to out-of-pocket spending (e.g., a state of the world where the return to out-of-pocket spending is higher because the individual has chosen to forgo valuable medical treatment due to under insurance). The return to out-of-pocket spending is measured by \( E_{\theta|m} \left[ \frac{u_h}{E[u_c]} \frac{d\tilde{h}}{dm} \right] / \frac{\partial x}{\partial m} \); the marginal product of medical spending on health, \( \frac{d\tilde{h}}{dm} \), is translated into consumption units by multiplying by \( \frac{u_h}{E[u_c]} \), and then translated into a return to out-of-pocket spending by dividing by the private cost of medical spending, \( \frac{\partial x}{\partial m} \). As was the case with the consumption first-order approach, the first term between parentheses in equation (11) measures the value of money in the current state of the world relative to its average value, and the second term between parentheses measures by how much Medicaid relaxes the individual’s...
The health first-order condition approach also requires only a partial specification of the utility function - this time over health rather than consumption - and once again does not require us to estimate how the individual allocates the marginal relaxation of the budget constraint between increased consumption and health.

**Comment: Endless arguments** A key distinction between the complete-information and the first-order condition approaches comes from the fact that the first-order condition approach allows one to consider marginal utility over any **one** argument of the utility function. The complete-information approach, by contrast, 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 might be conjectured to be impacted by health insurance (such as leisure, future consumption, children’s outcomes, etc.), we would also need to estimate the impact of the program 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.

### 2.2.4 From marginal to non-marginal welfare analysis

The first-order condition approaches naturally provide measures of marginal welfare impacts, \( \frac{d\gamma(q)}{dq} \). We arrive at our non-marginal estimate of the total welfare impact of Medicaid, \( \gamma(1) \), by integrating with respect to \( q \):

\[
\gamma(1) = \int_0^1 \frac{d\gamma(q)}{dq} dq,
\]

which follows from the fact that \( \gamma(0) = 0 \), by definition.

Figure 1 illustrates the integral computation, with the solid line representing \( \frac{d\gamma(q)}{dq} \), and \( \gamma(1) \) being the area under that curve. We have drawn \( \frac{d\gamma}{dq} \) downward sloping, assuming that the first unit of Medicaid is more valuable than the last unit. The figure depicts \( \frac{d\gamma}{dq}(1) > 0 \) (rather than \( \frac{d\gamma}{dq}(1) = 0 \)) because \( \gamma \) measures not only the value of the reallocation of resources across states of the world (a “pure-insurance” effect) but also the value to the recipient of the expected transfer of resources from Medicaid (a “transfer” term).

In principle, computing \( \gamma(1) \) from equation (12) requires knowledge of the causal impact of Medicaid on the joint distribution of \( \frac{\partial x}{\partial q} \) and of the relevant marginal utility throughout the path from \( q = 0 \) to \( q = 1 \) (in order to compute \( \frac{d\gamma}{dq} \) for values of \( q \) between 0 and 1). In practice, we do not observe \( q \in (0, 1) \). Therefore, we will require an additional statistical interpolation assumption.

---

15If the individual is at a corner solution with respect to medical spending, then the first term between parentheses in equation (11) is less than the value that the individual puts on money in that state of the world (which, after all, is why the individual chooses to have zero medical spending in that state of the world and, instead, spends all resources on the consumption of other goods). This implies that corner solutions in medical spending will lead equation (11) to be biased downwards.
to implement the first-order condition approaches.

**Assumption 3. (Linear Approximation)** The integral expression for $\gamma(1)$ in equation (12) is well approximated by:

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

Assumption 3 allows us to use estimates of $\frac{d\gamma(0)}{dq}$ and $\frac{d\gamma(1)}{dq}$ to form estimates of $\gamma(1)$. This approximation is illustrated by the dashed line in Figure 1. This is an important difference relative to the complete-information approach which, because it specifies a full utility function, can deliver non-marginal welfare estimates directly. In contrast, the first-order approaches follow the spirit of Harberger’s classic triangle (Harberger (1964)[34]) and approximate non-marginal welfare statements using statistical interpolations.

**Comment: liquidity effects** Figure 1 is also helpful for thinking about the welfare relevance of liquidity effects of health insurance, which has received some attention in the previous literature. In particular, Nyman (1999a[39], 1999b[40]) suggests 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. As a result, he argues, welfare analysis of health insurance requires decomposing the effects of health insurance on medical spending into income (or liquidity) effects and substitution effects, the former being a benefit and the latter imposing costs.

Conceptually, our formulas capture any welfare benefits that come via relaxation of liquidity constraints without decomposing the impact on medical spending into income and substitution effects. In the complete-information approach, these benefits are captured through the causal effects of Medicaid on health and consumption; if insurance enables access to (lumpy) medical procedures with large health values, the complete-information approach will measure and value the resulting health improvements. In the first-order condition approach, the value of additional liquidity provided by Medicaid is valued by the fact that insurance will bring resources to states of the world with high marginal utilities of consumption, resulting potentially from the relaxation of the liquidity constraint that would otherwise have occurred after incurring large medical expenses. But one does not need to isolate the impact of liquidity per se on behavior in order to capture this.\(^\text{16}\)

In practice, however, our imposition of the linear approximation to the integral in equation (12) may cause us to miss some of the value from liquidity in the first-order condition approaches. To see this, consider an extreme example in which expenses are sufficiently lumpy and individuals are

\(^{16}\text{Although the first-order condition approach requires individuals to equalize the marginal cost and marginal benefit of additional medical spending, we did not require concavity in the health production function, and we allow for insurance to affect medical spending in a discontinuous or lumpy fashion. Non-concavities in the health production function and non-convexities in the out-of-pocket spending schedule could lead to discontinuities in the marginal utilities (e.g., the marginal utility of consumption may jump up at the point of deciding to increase medical spending by a discontinuous amount in order to undergo an expensive medical procedure), but the equation for $\gamma(q)$ in integral form will remain continuous because, when the individual is at the margin of undertaking the jump, the individual will be indifferent to undertaking the jump or not.}\)
sufficiently liquidity constrained that the first unit of coverage is too small to allow individuals to purchase any medical care. Hence, there is no variation in the marginal utility of consumption across states of the world for the first unit of Medicaid coverage, because the first unit provides no marginal insurance value. However, a sufficiently large price reduction in the cost of medical procedures, say at \( q = 0.4 \), may allow the individual to purchase the expensive medical procedure. As a result, \( \frac{d\gamma}{dq} \) in Figure 1 would jump up once \( q = 0.4 \). As \( q \) increases beyond 0.4, the marginal insurance value declines because more complete insurance reduces the variation in the marginal utility of consumption across states of the world. The linear approximation in Figure 1 would not capture the relatively large values of \( \frac{d\gamma}{dq} \) that occur for intermediate values of \( q \) and would therefore underestimate the welfare effect of Medicaid on the recipient. In contrast, the complete-information approach would capture the full value of Medicaid, including value stemming from the liquidity it provides.

2.3 Decomposition

We briefly discuss decompositions of the marginal welfare impact on the recipient into two components: a transfer term and a pure-insurance term. Empirical implementation of the first-order condition approaches will be based on estimating each of these components separately.

2.3.1 Decomposition of first-order condition approaches

For the consumption first-order condition approach, the decomposition is:

\[
\frac{d\gamma(q)}{dq} = E \left[ \frac{u_c}{E[u_c]} \left( -\frac{\partial x}{\partial q} \right) \right] = E \left[ -\frac{\partial x}{\partial q} \right] + Cov \left[ \frac{u_c}{E[u_c]} \left( -\frac{\partial x}{\partial q} \right) \right] \tag{13}
\]

and similarly for the health first-order condition approach,

\[
\frac{d\gamma(q)}{dq} = E \left[ -\frac{\partial x}{\partial q} \right] + Cov \left[ E_{\theta|m} \left[ \frac{u_h}{E[u_h]} \frac{dh}{d\theta} \right], \left( -\frac{\partial x}{\partial q} \right) \right] \tag{14}
\]

**Transfer term**  The transfer term, \( E \left[ -\frac{\partial x}{\partial q} \right] \), measures the recipients’ valuation of the expected transfer of resources from the rest of the economy to them. Using equation (4), we can write the transfer term as:
\[ E \left[ -\frac{\partial x}{\partial q} \right] = E \left[ x(0,m(q;\theta)) - x(1,m(q;\theta)) \right]. \]  

(15)

In other words, at a given value of \( q \), the value of the transfer term is the expected difference in out-of-pocket spending between being fully covered by Medicaid and not being covered by Medicaid, holding medical spending constant at that value of \( q \). Note that \(-\frac{\partial x}{\partial q}\) is not a behavioral response to the insurance. Instead, it depends mechanically on the program parameters of Medicaid (as captured by the out-of-pocket spending schedule \( x(q,m;\theta) \)) and the distribution of medical spending \( m \). However, the estimate of the welfare effect from Medicaid (i.e., \( \gamma(1) \) in equation (12)) is based on the values of \(-\frac{\partial x}{\partial q}\) for individuals with and without Medicaid, which requires a causal estimate of Medicaid on the distribution of \( m \).

Estimation of the transfer term via equation (15) requires no assumptions about the utility function; it is based solely on causal estimates of the impact of the program on medical spending and a “pure program parameter” of how medical spending maps into out-of-pocket spending for a given level of insurance. We therefore consider an estimate of the transfer term via the first-order condition approach as a a relatively robust, lower bound (i.e., ignoring the insurance component) estimate of the value of Medicaid.

**Pure-insurance term** The “pure-insurance” or “covariance” term measures the benefit of reallocating resources (i.e., relaxing the recipient’s budget constraint) across different states of the world, \( \theta \). The movement of these resources is valued using the relative marginal utility of income in each state. In the consumption first-order approach, the relative marginal utility of income is evaluated using the marginal utility of consumption in that state; the health first-order approach evaluates it in terms of the additional health it allows the consumer to buy in that state. The logic of the covariance term is thus highly related to the broad insights from the the asset-pricing literature - where the introduction of new financial assets can be valued using their covariance with the marginal utility of consumption, which itself can have multiple representations, such as in the classic consumption CAPM (see, e.g., Cochrane (2005)[15]). The covariance term plays a key role in overcoming the requirement in the complete-information approach of having to specify a utility function over all variables on which Medicaid has an impact.

---

\(^{17}\)This is analogous to moving resources across people in the optimal tax formulas, where the welfare impact of increasing the marginal tax rate on earnings financed by a decrease in the intercept of the tax schedule is given by the covariance between earnings and the social marginal utility of consumption (see, e.g., Piketty and Saez (2012) equation (3)[41]).

\(^{18}\)In this sense, our analysis is similar in spirit to efforts of Koijen et al. (forthcoming) [38] to model the individual’s insurance portfolio choice problem as an optimal asset-allocation problem. In the language of the asset-pricing literature, the health first-order condition approach values the insurance program using a “health kernel” and the consumption first-order condition approach values the insurance program using a “consumption kernel,” as in the standard consumption CAPM model, with the modification that there are moral hazard effects of the provision of insurance.
2.3.2 Decomposition of the complete-information approach

The complete-information approach can also be decomposed into several components, which may provide some useful intuition. We rewrite the terms in equation (9) to arrive at the following expression for the marginal welfare impact of Medicaid:

\[
\frac{d\gamma(q)}{dq} = E\left[\frac{u_c}{E[u_c]} \frac{dc}{dq}\right] + E\left[\frac{u_h}{E[u_c]} \frac{dh}{dq}\right].
\]

(16)

The welfare impact on recipients of marginal increases in Medicaid consists of two components. The first component, \(E\left[\frac{u_c}{E[u_c]} \frac{dc}{dq}\right]\), takes how Medicaid changes consumption across states of the world, \(\frac{dc}{dq}\), and values these changes by the marginal utility of consumption in the corresponding state of the world, \(\frac{u_c}{E[u_c]}\). The second component, \(E\left[\frac{u_h}{E[u_c]} \frac{dh}{dq}\right]\), takes how Medicaid changes health across states of the world, \(\frac{dh}{dq}\), and values these changes by the marginal utility of health in the corresponding state of the world, \(\frac{u_h}{E[u_c]}\).

As in the first-order condition approaches, we can further decompose the welfare impact on the recipient operating through consumption or operating through health into transfer and “pure insurance” terms. In Appendix A.2, we decompose the welfare impact on the recipient into two transfer terms, corresponding to increases in the mean values of consumption and medical spending, and two insurance terms, corresponding to the value of bringing consumption into states of the world with higher marginal utilities of consumption and bringing medical spending into states of the world with higher health returns to medical spending.

3 Application: The Oregon Health Insurance Experiment

3.1 Setting and data

We apply these approaches to welfare analysis of the Medicaid expansion that occurred in Oregon in 2008 via a lottery. The lotteried program, called OHP Standard, covers low-income (below 100 percent of the federal poverty line), uninsured, adults (aged 19-64) who are not categorically eligible for OHP Plus, Oregon’s traditional Medicaid program. OHP Standard provides comprehensive medical benefits with no patient cost-sharing and low monthly premiums ($0 to $20, based on income). We focus on the welfare effects of Medicaid coverage after approximately one year.

In early 2008, the state opened a waiting list for the previously closed OHP Standard. It randomly selected approximately 30,000 of the 75,000 people on the waiting list to have the opportunity – for themselves and any household members – to apply for OHP Standard. Following the approach of previous work on the Oregon experiment, we use random assignment by the lottery.

---

19 Throughout, we use the term “Medicaid” to refer to coverage by either OHP Standard or OHP Plus. In practice, the increase in Medicaid coverage due to the lottery comes entirely from an increase in coverage by OHP Standard (Finkelstein et al. (2012) [27]).
Winning the lottery increased the probability of being on Medicaid at any time during the subsequent year by about 25 percentage points. This “first stage” effect of lottery selection on Medicaid coverage is below one because many lottery winners either did not apply for Medicaid or were deemed ineligible. All of the objects we calculate are estimated for the compliers - i.e., all those who are covered by Medicaid if and only if they win the lottery (see, e.g., Angrist and Pischke (2009) [2]). Thus in our application “the insured” ($q = 1$) are treatment compliers and “the uninsured” ($q = 0$) are control compliers.

The data used here from the Oregon Health Insurance Experiment were previously analyzed by Finkelstein et al. (2012)[27] and are publicly available at www.nber.org/oregon. Data on Medicaid coverage ($q$) are taken from state administrative records. All of the other data elements are derived from information supplied by approximately 15,500 respondents to mail surveys sent about one year after the lottery to individuals who signed up for the lottery.

Table 1 presents descriptive statistics on the data from the Oregon Health Insurance Experiment. The first column reports results for the full study population. Columns 2 and 3 report results for the treatment compliers and control compliers respectively. 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 = 0.14). Panel B presents summary statistics on our key outcome measures, which we now discuss.

**Health $h$**

In our baseline specification, we measure health ($h$) as a binary variable for whether the individual reports his health to be excellent, very good, or good (as opposed to fair or poor); we explore sensitivity to other health measures below. About 61 percent of treatment compliers ($q = 1$) and 47 percent of control compliers ($q = 0$) report their health to be excellent, very good, or good.

**Medical spending $m$**

Following Finkelstein et al. (2012)[27], we estimate total annual medical spending for each individual based on their self-reports of utilization of prescription drugs, outpatient visits, ER visits, and inpatient hospital visits, weighting each type of use by its average resource cost among the low-income publicly insured adults in the Medical Expenditure Survey (MEPS). On average, annual medical spending is about $2,700 for control compliers ($q = 0$) and about $3,600 for treatment compliers ($q = 1$).

---

20Finkelstein et al. (2012) [27] provides more details on the lottery, and supporting evidence on the assumptions required to use the lottery as an instrument for Medicaid coverage. Previous work has used the the lottery as an instrument for Medicaid to examine the impact of Medicaid on health care utilization, financial well-being, labor market outcomes, health, and private insurance coverage (Finkelstein et al., (2012) [27], Baicker et al., (2013) [6], (Baicker et al. (2014) [4]), and Taubman et al., (2014) [43]).
Out-of-pocket spending $x$

We measure annual out-of-pocket spending as self-reported out-of-pocket medical expenditures in the last 6 months, multiplied by two. Since Medicaid in Oregon has zero out-of-pocket cost sharing, no or minimal premiums, and comprehensive benefits, we assume in our baseline analysis that the insured ($q = 1$) have zero out-of-pocket spending and assume that any positive reported spending reflects measurement error. We explore sensitivity below to conducting our welfare analysis for the case where Medicaid does not provide full insurance and the insured’s out-of-pocket spending reflects their true expenses. Average annual out-of-pocket medical expenditures for control compliers ($q = 0$) is $\$481$; median out-of-pocket spending for this group is zero.$^{21}$

Consumption $c$

The difficulty in obtaining high-quality consumption data is a pervasive problem for empirical research on a wide array of topics. Ours is no exception. Consumption data are not available for participants in the Oregon study. As a result, we take two approaches to measuring consumption.

Approach #1: Proxy consumption using out-of-pocket expenditure

We approximate $c$ as the difference between income and out-of-pocket spending. We use the definition of out-of-pocket spending above. For income, individuals reported their 12-month household income in bins. To calculate per capita annual income ($\bar{y}$), we first compute average annual household income by using income-bin midpoints and a top-coded value of $\$50,000$. We then divide this household income measure by the total number of family members (adults and children) in the household.

Average per capita income ($\bar{y}$) is $\$3,808$ per year for the compliers in our sample. While this is quite low, recall that compliers must be below the federal poverty line. In 2009, the federal poverty line reflected per capita income of between $\$5,513$ and $\$10,830$ for family sizes of 4 individuals to 1 individual.$^{22}$ By using average income $\bar{y}$ instead of observed individual income, our approach assumes away any direct impact of Medicaid on income, as well as heterogeneity across individuals in income.$^{23}$

We thus define consumption as:

$$c = \bar{y} - x.$$  

(17)

Because there is unavoidable measurement error in this approach to measuring $c$, and because

---

$^{21}$It is worth noting that mean out-of-pocket spending for the uninsured is far below their mean medical spending of $\$2,700$. We discuss the implications of this difference between out-of-pocket spending and medical spending for the uninsured in Section 4.3 below, where we also show that it is not an artifact of our setting but rather a more general empirical finding.

$^{22}$See http://aspe.hhs.gov/poverty/09poverty.shtml

$^{23}$Prior analysis of the Oregon Health Insurance Experiment showed no evidence of a direct impact of Medicaid on income (Finkelstein et al. (2012) [27], Baicker et al. (2014)[4]). Heterogeneity of income is limited by the fact that the program requires income below the federal poverty line; while there is undoubtedly still some cross-sectional heterogeneity in income, as a practical matter we suspect that our measurement of it has a high noise-to-signal ratio. For example, about 13 percent of respondents report zero income.
welfare estimates are naturally sensitive to \( c \) at low values, we follow standard procedure for ruling out implausibly low values of \( c \) (e.g., Brown and Finkelstein (2008) [9], Hoynes and Luttmer (2011) [36]) by imposing an annual consumption floor. Our baseline analysis imposes a consumption floor of $1,000 per capita per year, which we implement by capping out-of-pocket expenditure at \( \bar{y} - c_{floor} \). In the sensitivity analysis below, we consider how the results are affected by assuming higher values of average income \( \bar{y} \), and thus of average consumption, than reported in these data. We also explore sensitivity to the assumed value of the consumption floor.

**Approach #2: Measure consumption using national data from the CEX**

A concern with our consumption proxy is that it 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 or have other ways of smoothing consumption, this approach may overstate the consumption smoothing benefits of Medicaid. Another concern with our consumption proxy is that if average income is misreported, we may mis-estimate Medicaid’s consumption benefits. Ideally, we would measure consumption directly.

Although we do not observe consumption for the Oregon sample, we can observe consumption for low-income adults in the Consumer Expenditure Survey (CEX). We use the CEX to estimate the relationship between non-medical consumption and out-of-pocket medical expenditure for adults below the federal poverty line without formal insurance \( (q = 0) \), in other words, to estimate the covariance term in equation (13) at \( q = 0 \). Because the CEX requests information only on the health insurance status of the household head, we restrict the sample to single adults with no children in the household so that we can accurately measure insurance status. Appendix A.5 provides more detail on the data and our sample definition.

Because we do not have any identifying variation in \( q \) in the CEX to allow us to estimate what the covariance term would be at \( q = 1 \), we instead assume (as we did in the consumption proxy approach) that consumption is constant at \( q = 1 \), and hence the covariance term is 0. This enables us to implement the consumption first-order condition approach using the CEX data, but not the complete-information approach (which requires identifying variation in \( q \) to estimate what consumption would be at \( q = 1 \)).

### 3.2 Implementation assumptions

#### 3.2.1 Complete-information approach

We assume that the utility function takes the following form:

**Assumption 4.** Full utility specification for the complete-information approach.

The utility function has the following form:

\[
    u(c, h) = \frac{c^{1-\sigma}}{1-\sigma} + \phi h,
\]
where $\sigma$ denotes the coefficient of relative risk aversion and $\phi = \tilde{\phi}/E[c^{-\sigma}]$ denotes the marginal value of health in units of consumption.

Utility has two additive components: a standard CRRA function in consumption $c$ with a coefficient of relative risk aversion of $\sigma$, and a linear term in $h$.\textsuperscript{24}

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

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

where the expectation is taken over all states of the world $\theta$.

We use equation (18) to solve for $\gamma(1)$. This requires observing the distributions of consumption and mean health outcomes that occur if the individual were on Medicaid ($c(1; \theta)$ and $h(1; \theta)$) and if he were not ($c(0; \theta)$ and $h(0; \theta)$). 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) [2]).

The assumptions we have made about the utility function reduce the set of potential outcomes we need to estimate. The additivity of utility from consumption and health allows us to estimate the marginal consumption and marginal health distributions under each insurance status; imposing complementarities, such as estimated in Finkelstein et al. (2013) [25], would require estimates of the causal effect of insurance on joint distributions. This would be empirically feasible but more difficult to implement. The linearity assumption in $h$ allows us to restrict our health estimation to average health under each insurance status. By contrast, allowing for curvature in utility over consumption – to reflect the fact that individuals are risk averse – requires that we estimate the distribution of consumption under each insurance status. Fortunately, we only require the impact of the program on the distributions (as opposed to the distribution of marginal effects conditional on $\theta$), which can be readily estimated using standard quantile treatment effect estimators.

For our baseline analysis, we assume a coefficient of relative risk aversion $\sigma$ of 3. We arrive at a baseline assumption regarding $\phi$ as follows. We (crudely) convert the estimated effect of Medicaid on self-reported health measure (see Table 1) into an estimated effect on 10-year life expectancy based on the cross-sectional variation in life expectancy between low-income adults with different self-reported health in the National Health Interview Survey.\textsuperscript{25} We further assume a baseline value of a statistical life year (VSLY) in our population of $\$25,000.\textsuperscript{26} Combining these assumptions yields

\textsuperscript{24}We assume that $\phi$, the marginal value of health in units of consumption, is constant across $\theta$, as has been done in the empirical literature that has tried to estimate it.

\textsuperscript{25}We compare subsequent 10-year survival for low-income (below two times the federal poverty line) adults (aged 19-64) who report their health as excellent, very good or good to those who report fair or poor, using the linked mortality public-use data files of the National Health Interview Surveys from 1986-1996. We control in our analysis for year, gender, race, age and education level, but recognize that we estimate an association, not a causal effect. We find that low-income adults who report being in good, very good, or excellent health have a 0.49 year higher 10-year survival than low-income adults who report their health as fair or poor. Because we examine survival over only a 10-year window (due to data constraints), our estimate of $\phi$ will be biased down if high self-reported health results in survival gains beyond this 10-year window. On the other hand, we assume that survival gains from high self-reported health are additive, and our estimate of $\phi$ will be biased upwards if in fact these survival gains are subadditive.

\textsuperscript{26}The welfare analysis requires a measure of the VSLY that equals the (hypothetical) willingness to pay by the
a value for φ, the value of reporting excellent, very good, or good health (rather than fair or poor) of $12,250.

3.2.2 First-order condition approaches

We estimate the transfer and pure-insurance terms in equations (13) or (14) and sum these two terms to estimate the marginal welfare effect of increasing Medicaid benefits. We do this calculation separately for the uninsured and for the insured, which yields \( \frac{dx}{dq} (0) \) and \( \frac{dx}{dq} (1) \), respectively. We then use the linear approximation in Assumption 3, illustrated in Figure 1, to construct an estimate of \( \gamma (1) \).

**Transfer term** The transfer term is common to both the consumption first-order condition approach and the health first-order condition approach (see equation (15)). Because of our baseline assumption of \( x (1, m(q; \theta)) = 0 \), the transfer term can be re-written as:

\[
E \left[ - \frac{\partial x}{\partial q} \right] = E \left[ x (0, m(q; \theta)) \right],
\]

which is the average out-of-pocket spending for someone without Medicaid if she had the distribution of medical spending corresponding to insurance level \( q \).

**Pure-insurance term** The pure-insurance term in both first-order condition approaches requires estimation of the marginal relaxation of the budget constraint due to Medicaid, \( -\frac{\partial x}{\partial q} \). Using our baseline assumption of \( x (1, m(q; \theta)) = 0 \) and partially differentiating equation (4) with respect to \( q \), we find:

\[
- \frac{\partial x}{\partial q} = x (0, m(q; \theta)).
\]

In addition, we impose one of two alternative assumptions about the utility function to define the pure-insurance term in each first-order condition approach.

**Assumption 5. Partial utility specification for the consumption first-order condition approach.**

The utility function has the following form:

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

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

recipients out of their own income. We arrive at this figure by taking Cutler’s (2004) choice of $100,000 for the VSLY, and adjusting this figure for the fact that median household income in our population is $13,000, in contrast to the median of $50,000 in the population used to estimate the VSLY. In other words, we assume that the VSLY scales linearly with income.
We use the same baseline assumption for $\sigma$ as in the complete-information approach. Given Assumption 5 and the definition of $-\frac{\partial x}{\partial q}$ in equation (20), the pure-insurance or covariance term in the consumption first-order condition in equation (13) can be written as:

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

(21)

**Assumption 6.** Partial utility specification for the health first-order condition approach.

The utility function has 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.

Given Assumption 6 and the definition of $-\frac{\partial x}{\partial q}$ in equation (20), the covariance term in the health first-order condition in equation (14) can be written as:

$$Cov\left(\frac{E_{\theta|m}\left[\frac{\partial h}{\partial m}\right]}{\frac{\partial x}{\partial m}}\phi, x(0, m(q;\theta))\right).$$

(22)

The term $\phi \equiv \frac{\tilde{\phi}}{E[p(c)]}$ is, as in the complete-information approach, the marginal value of health in units of consumption, and we use the same baseline assumption for $\phi$ as in the complete-information approach.

### 4 Results

#### 4.1 Complete-information approach

The complete-information approach requires us to estimate health outcomes and the distribution of consumption for control compliers ($q = 0$) and for treatment compliers ($q = 1$). We estimate that the probability that self-reported health is excellent, very good or good (as opposed to fair or poor) is 47 percent for control compliers and 61 percent for treatment compliers (see Table 1).

To estimate the impact of Medicaid on the distribution of $c$, we first estimate the impact of Medicaid on the distribution of out-of-pocket spending, and then map out-of-pocket spending to consumption based on equation (17). To estimate the impact of Medicaid on the distribution of out-of-pocket spending, 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. Appendix A.1 describes these techniques in more detail, and also reports that the parametric model fits the data quite well.

The log-normal model allows for positive probability of very high out-of-pocket expenditures. As mentioned in Section 3.1, we impose a consumption floor by capping out-of-pocket spending drawn
from the log-normal distribution at \( \bar{y} - c_{\text{floor}} \), where \( \bar{y} \) denotes income and \( c_{\text{floor}} \) the consumption floor, which is $1,000 in our baseline specification; the cap binds for less than 5 percent of control compliers.

In order to be consistent with our treatment of out-of-pocket spending in this consumption measure, we impose these two adjustments throughout, wherever we use out-of-pocket spending estimates for control compliers. As a result, the mean value of \( x \) among control compliers is $489, instead of $481 as in Table 1. The adjustments are inconsequential for our use of out-of-pocket spending when we use it on its own. 27 Figure 2 shows the resultant distributions of consumption for the the control compliers (\( q = 0 \)) and treatment compliers (\( q = 1 \)). Average consumption for control compliers (\( q = 0 \)) is $3,320 with a standard deviation of $768. For treatment compliers (\( q = 1 \)), consumption is simply average income, $3,808, since by assumption \( x(1,m) = 0 \). The difference between the two lines in the figure shows the increase in consumption due to Medicaid for the compliers. On average, Medicaid increased consumption by $489.

We use these estimates to evaluate the welfare effect on recipients by solving for \( \gamma(1) \) in equation (18). The first column of Table 2 shows the results. We estimate that Medicaid recipients receive a welfare gain of $1,576 per person per year from Medicaid using the complete-information approach.

The remaining rows decompose this welfare impact into components. We use the additive separability of the utility function to separately estimate the welfare gain due to consumption ($1,111) and then infer the welfare gain due to health ($465) as the difference between \( \gamma(1) \) and the welfare gain due to consumption. 28 Within the consumption gain of $1,111, we can further separate the welfare gain due to the consumption transfer - which is simply the impact of Medicaid on average consumption ($489) - and the remainder ($622), which represents the welfare gain from the pure-insurance component operating through consumption smoothing. 29 For health, we estimate a transfer value of $205, 30 leaving an additional insurance value from health of $260, implying that Medicaid brings resources to state of the world with a higher return to medical spending. Appendix A.2 provides additional implementation details of this decomposition.

Overall, this decomposition suggests that over two-thirds of the welfare gain from Medicaid operates through the impact on consumption (particularly the insurance component of the consumption benefit) whereas less than a third can be attributed to the impact on health. The results

27 We verified (in results not shown) that if we do not make the adjustments for out-of-pocket spending when used on its own (rather than as an input into one of our consumption measure), our main results concerning the value of Medicaid to recipients per dollar of government spending are unaffected; both the welfare to the recipients and the estimated program costs increase slightly, and the ratio is unchanged.

28 Because of the curvature of the utility function, the order of operations naturally matters. In practice, however, it does not affect our basic finding from the complete-information approach that most of the welfare gains from Medicaid operate through consumption rather than health. If we instead directly estimate the welfare gain due to health and then infer the welfare gain due to consumption based on the difference between \( \gamma(1) \) and the welfare gain due to health, we estimate a welfare gain due to consumption of $1,195 and a welfare gain due to health of $382.

29 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) [26] to estimate the consumption-smoothing value of the introduction of Medicare.

30 In other words, we estimate that the health value of the average increase in medical spending of $885 is $205.
also suggest that a little less than half of the welfare benefit to Medicaid recipients comes from the transfer component, with slightly more than half coming from Medicaid’s ability to move resources across states of the world.

4.2 First-order condition approaches

**Transfer component**  As shown in equation (19), the transfer term is defined using the out-of-pocket spending schedule of the uninsured, \( E[x(0, m(q; \theta))] \), evaluated using the distribution of \( m \) that corresponds to a given \( q \). For the control compliers (\( q = 0 \)), the transfer term is simply their average out-of-pocket spending. We estimate that this is $489.

For the treatment compliers (\( q = 1 \)), the transfer term corresponds to the average out-of-pocket spending they would have incurred, at their actual level of medical spending, if they had faced the out-of-pocket spending schedule of the uninsured. We approximate the out-of-pocket spending schedule for the uninsured \( x(0, m) \) by assuming that it is linear in \( m \) and estimating price as the ratio of mean out-of-pocket spending to mean total spending for the control compliers (i.e., \( \frac{\partial x}{\partial m} \bigg|_{q=0} = \frac{E[x(0, m(0; \theta))]}{E[m(0; \theta)]} \)). This yields a price for the uninsured, \( \frac{\partial x}{\partial m} \bigg|_{q=0} \), of 0.18. With the assumption of a constant price for the uninsured, we can write:

\[
E[x(0, m(1; \theta))] = E[x(0, m(0; \theta))] + \left( \frac{\partial x}{\partial m} \bigg|_{q=0} \right) E[m(1; \theta) - m(0; \theta)],
\]

where \( \left( \frac{\partial x}{\partial m} \bigg|_{q=0} \right) E[m(1; \theta) - m(0; \theta)] \) is the increased out-of-pocket spending the individual would have had if she faced the uninsured price schedule but chose to increase medical expenses to \( m(1; \theta) \) instead of \( m(0; \theta) \). We estimate \( E[m(1; \theta) - m(0; \theta)] = $885 \), so that the transfer component is roughly 0.18 * $885 ≈ $160 higher at \( q = 1 \) than at \( q = 0 \). Averaging the transfer value at \( q = 0 \) and \( q = 1 \), we estimate a transfer component of $568 per Medicaid recipient. Note that the transfer component is the same for the health and consumption first-order conditions because its estimation does not require any specification of the utility function.

**Consumption first-order condition approach #1 (consumption proxy)**  We estimate the pure-insurance value using equation (21). At \( q = 0 \), this is the covariance between the marginal utility of consumption (normalized by its average) and the state-contingent marginal transfer provided by Medicaid; this state-contingent marginal transfer is equal to the out-of-pocket spending that one would have in the absence of Medicaid, holding medical spending constant. Estimation of the pure insurance term at \( q = 0 \) therefore requires estimates of the distribution of out-of-pocket spending and the distribution of consumption for control compliers; we use the estimates we described above in implementing the complete-information approach. At \( q = 1 \), our assumption that \( x(1, m) = 0 \) together with our definition of consumption in equation (17) immediately implies that the marginal utility of consumption is constant, and hence the pure-insurance value of Medicaid is 0 on the margin; we relax this assumption in the sensitivity analysis below. Following the linear approximation in Assumption 3, the total pure-insurance component is therefore one-half of what
we estimate at $q = 0$, or $678.

Combining the estimate of the pure-insurance component with the transfer component yields an estimate of the welfare benefit of Medicaid to recipients ($\gamma(1)$) of $1,247 per recipient. These results are shown in Table 2, column II. Once again, just under half of the welfare value comes from the transfer component, with slightly more than half coming from Medicaid’s ability to move resources across states of the world.

**Consumption first-order condition approach #2 (CEX consumption measurement)**

Once again, we model Medicaid as providing full insurance, so that the pure-insurance value is 0 at $q = 1$. We use the consumption data among the uninsured from the CEX to estimate the pure-insurance term at $q = 0$. We estimate average consumption for the uninsured of $13,541 (standard deviation = $7,451).\textsuperscript{31} This is substantially higher than our estimate of $3,320 for mean consumption for control compliers using the consumption proxy approach. This may reflect the different samples, but also likely reflects the well-known problem in the Consumer Expenditure Survey (CEX) that income tends to be underreported, and thus average annual expenditures exceed income for some demographic groups.\textsuperscript{32} We discuss below how this may affect our estimates across the two approaches.

In principle, the pure-insurance term at $q = 0$ can be directly estimated in the CEX data from the covariance in the data between $c - \sigma$ and out-of-pocket medical spending for the uninsured. In practice, however, the raw data show a negative covariance (i.e., higher non-medical consumption is correlated with higher out-of-pocket medical spending among the uninsured). This could be an accurate measure of the covariance if it were driven, say, by unobserved income so that those with higher consumption had higher medical spending. In this case, the negative covariance would reflect the fact that a reduction in the marginal price of health expenditure is bringing resources to states of the world with a lower marginal utility of consumption, and the value of Medicaid would actually be below its transfer component. However, in Appendix A.5 (and Appendix Table A.3) we illustrate that this covariance is less negative for the uninsured than the insured, which suggests that the covariance term may be biased from measurement error that induces a negative correlation between $c - \sigma$ and $x$. Appendix A.5 provides a measurement-error model that shows how one can use the implication that this covariance should be zero if insurance is full at $q = 1$ to back out the unbiased covariance term at $q = 0$. In practice, this means using a simple difference in the observed covariance term for the uninsured and insured as a measure of the unbiased covariance for the uninsured ($q = 0$), which we estimate to be $252.

Column (III) presents the results. Relative to the results in the first two columns, the pure-insurance value from the covariance term is an order of magnitude lower, at $126. Using the same estimate of the transfer term as described above, this implies a total welfare impact to recipients

\textsuperscript{31}We impose the same baseline consumption floor as in the consumption proxy approach, but it never binds in the CEX data.

\textsuperscript{32}See see: http://www.bls.gov/cex/faq.htm##q21.
of $694.\textsuperscript{33} Under this approach, about four-fifths of the value of Medicaid to recipients comes from the transfer component, and only about one-fifth comes from its ability to move resources across states of the world.

The CEX consumption measure thus yields a substantially lower estimate of the “pure insurance” component of the value of Medicaid (column III) than the consumption proxy (column II).\textsuperscript{34} This may reflect the fact that individuals have access to additional forms of informal insurance that prevent a $1 increase in out-of-pocket spending from translating into a $1 decrease in consumption, as is assumed in the consumption proxy approach. It is also possible that we underestimate the covariance between marginal utility of consumption and out-of-pocket medical spending using the CEX data, despite our attempts to fit the measurement-error model, or that our sample of low-income uninsured adults in the CEX data is not representative of control compliers in the Oregon Experiment sample.\textsuperscript{35}

**Health first-order condition approach**  As in the consumption first-order condition approach, we assume that out-of-pocket spending is zero at \( q = 1 \), which implies that the pure-insurance component is zero at \( q = 1 \). To calculate the pure-insurance component of the health first-order condition approach at \( q = 0 \), we require an estimate of the marginal health return to out-of-pocket spending, \( \frac{\partial \tilde{h}}{\partial m} / \frac{\partial m}{\partial m} \) (see equation (22)).

Estimating the health production function \( \frac{\partial \tilde{h}}{\partial m} \) is notoriously challenging. Indeed, the literature has found it challenging enough to estimate a local average treatment effect for the impact of medical spending on health (see, e.g., Almond et al. (2010) for one approach [1]). In our case, the challenges are compounded by the fact that we must estimate heterogeneity in these returns across the values of the endogenous choice of medical spending.

We estimate the health returns to medical spending using the lottery as an instrument for medical spending. This assumes that the only way that Medicaid affects health is via an impact on medical spending; it thus precludes impacts of Medicaid on health resulting, for example, through increased mean consumption or reduced exposure to the risk of low consumption which might, for example, improve health by reducing stress. To estimate the returns to medical spending across

\textsuperscript{33} We use the transfer term estimated previously because estimating the transfer term in the CEX requires a causal estimate of the impact of Medicaid on \( m \), which we have in the Oregon data but not in the CEX data. By contrast, the covariance term in the consumption first-order condition, as we have implemented it, does not require a causal estimate of Medicaid on consumption because in our setting the covariance term is 0 at \( q = 1 \).

\textsuperscript{34} The value of Medicaid use the CEX consumption measure would be lower still if we had used the raw data (with negative covariances) as opposed to the measurement-error model.

\textsuperscript{35} The difference in estimates does not appear to reflect the fact that our direct consumption measure (unlike our consumption proxy measure) is limited to singles; the consumption proxy approach yields a somewhat higher estimates when limited to singles (results not reported). Interestingly, the lower insurance value using the direct consumption measurement approach also does not reflect the higher average consumption from this approach in the data (approximately $13,300 compared to approximately $3,300 in the consumption proxy approach). We find that raising average consumption in the consumption proxy approach (by raising average income) to the level in the direct consumption measurement approach actually increases the value of insurance in the consumption proxy approach (see Table 4, column XI below); this somewhat counter-intuitive result reflects the fact that in the presence of a consumption floor, increasing average consumption exposes the individual to more downside risk and can therefore increase the value of insurance.
values of the (endogenous) choice of medical spending $m$, we assume that heterogeneity in $m$ can be proxied using a set of observable variables $\theta^K$, and assume that the health production function is constant for all $m$ conditional on $\theta^K$.

Ideally, the information contained in $\theta^K$ would be the information that the individual uses when choosing to consume medical care relative to consumption. We therefore use measures of baseline medical and financial status for $\theta^K$. Appendix A.3 provides more detail on our implementation and estimates of this approach. We estimate the impact of medical spending on health separately for each of four values of $\theta^K$, instrumenting for medical spending with the Medicaid lottery. This provides an estimate of the health production function at each value of $\theta^K$. The estimates, shown in Appendix Table A.2, are all imprecise; none are statistically different from zero. However, the point estimates are consistent with the hypothesis that the value of insurance is higher for financially constrained individuals. Of course, our approach will be biased if we have not controlled for all of the state variables that go into the individual’s choice of the level of medical spending (which we readily admit is likely). In this case, our approach omits any value of insurance within each value of $\theta^K$, and thus likely underestimates the true value of insurance. However, it provides a parsimonious methodology for implementing the health first-order condition approach with our data. Its empirical limitations also highlight the importance of further work aimed at identifying not only the average return on medical spending, but also its heterogeneity.

To calculate the covariance term conditional on $\theta^K$, we estimate the distribution of out-of-pocket spending among control compliers conditional on $\theta^K$, which enters as the right-hand side of the covariance term in equation (22). Dividing the expected slope of the health production function conditional on $\theta^K$, $E \left[ \frac{\partial \tilde{h}}{\partial m} | \theta^K \right]$, by the estimated price of medical spending ($\frac{\partial x}{\partial m}$) of 0.2 yields the left-hand side of the covariance term: $E \left[ \frac{\partial \tilde{h}}{\partial m} | \theta^K \right] / \frac{\partial x}{\partial m}$. Estimation of the right hand size of the covariance term, $x(0, m(q; \theta))$ was described previously. We combine the estimates of the covariance term for each type $\theta^K$ by weighting them by the fraction of control compliers of each type $\theta^K$.

The results are shown in column IV of Table 2. Averaging the pure-insurance component estimated for $q = 0$ with a pure insurance component of zero at $q = 1$, we find that the pure-insurance component is $112. The fact that the pure-insurance component is positive implies that the insurance program tends to increase medical spending more in states of the world with higher marginal health returns to medical spending. Combining this pure-insurance value with the transfer term calculated above, we estimate a total welfare impact for Medicaid recipients from the health first-order condition approach of $680. Note that the standard error for this estimate is considerably higher than in any other approach, reflecting the considerable uncertainty in our estimate of the health production function. As with the consumption first-order condition approach based on the direct consumption measure, about four-fifths of the value of Medicaid to recipients comes from the transfer component.

\[36\] Specifically, we use $\text{Cov}_{\theta}[X,Y] = E_{\theta^K} [E_{\theta \mid \theta^K} [X,Y]] - E_{\theta} [X] E_{\theta} [Y]$. In other words, we calculate the first expectation of this covariance term first conditionally on $\theta^K$, and then we take the expectation of these conditional expectations.
4.3 Medicaid costs

To contextualize these estimates of Medicaid’s welfare benefits to recipients, we compare them to Medicaid’s resource costs. We denote the total resource costs of $q$ by $C(q)$. We normalize $C(0) = 0$, so the resource cost of Medicaid is given by $C(1)$. We focus on the resource costs coming from the increase in medical spending induced by insurance, $m(q; \theta) - m(0; \theta)$, and from the decrease in out-of-pocket spending due to insurance, $x(q, m(q; \theta)) - x(0, m(0; \theta))$. Hence,

$$C(q) = E[m(q; \theta) - m(0; \theta)] - E[x(q, m(q; \theta)) - x(0, m(0; \theta))].$$  \hspace{1cm} (24)

Who pays these resource costs? The government is an obvious payer. We let $G(q)$ denote government costs, which is given by:

$$G(q) = C(q) + N(q),$$

where $N(q)$ denotes potential net transfers in Medicaid from the government to non-recipients of Medicaid coverage, i.e., external parties that, in the absence of Medicaid, would have paid for medical spending that was not covered by the out-of-pocket spending of uninsured individuals. We normalize $G(0) = N(0) = 0$. Thus, $G(1)$ is the (per-recipient) causal impact of Medicaid on the government’s budget and $N(1)$ is the (per-recipient) causal impact of Medicaid on the budget of external parties. Since the government pays the medical bills for Medicaid recipients and Medicaid recipients have no out-of-pocket spending (i.e., $x(1, m) = 0$), the cost to the government is given by:

$$G(1) = E[m(1; \theta)].$$  \hspace{1cm} (25)

The net transfers to non-recipients are given by the amount of medical spending that went unpaid by the uninsured:

$$N(1) = E[m(0; \theta)] - E[x(0, m(0, \theta))].$$  \hspace{1cm} (26)

The identity of non-recipients across the economy is potentially quite complicated. The provision of uncompensated care by hospitals is a natural starting point; Garthwaite, Gross, and Notowidigdo (2015[30]) recently estimated that increases in Medicaid coverage lead to large reductions in such uncompensated care. Family members or others who previously provided uncompensated informal insurance may also be non-recipients who receive net transfers from Medicaid.\footnote{There are of course many other potential resource costs. For example, labor supply responses to Medicaid may impose fiscal externalities on the government via their impact on tax revenue. In the context of the Oregon Health Insurance Experiment, there is no evidence that Medicaid affected labor market activities (Baicker et al. (2014) [4]).}

\footnote{Another potential group to consider is the privately insured. While our framework takes crowd out of private insurance for Medicaid recipients into account in our estimates, such crowd out may also affect (with unknown sign) adverse selection in the private health insurance market and, hence, outcomes for non-recipients in that market. In the complete-information approach, such general equilibrium effects on non-Medicaid recipients can in principle be captured by estimating the impact of Medicaid on all utility-relevant arguments for non-recipients as well. Likewise, in the first-order condition approach, these general equilibrium effects can be captured by estimating the impact of}
The ultimate economic incidence of the transfers to non-Medicaid recipients is even more complicated; while some of the incidence may fall on the direct recipients of the net transfers, other parties bearing some of the incidence may include the privately insured, the government budget (for example, through reduced payments to providers for the provision of uncompensated care), or even the recipients themselves (for example, if reductions in unpaid medical debt improve their credit scores). In principle, one could trace through these incidences by estimating the impact of Medicaid on the welfare of other parties. Doing so requires additional causal estimates beyond what is readily available in our setting. In practice, we follow a simpler procedure that abstracts from any value that these transfers may deliver to non-recipients above or below their costs, and we simply sum up the size of the transfer that Medicaid induces to non-recipients, \( N(1) \).

The top panel of Table 3 summarizes our estimates of \( C(1), G(1) \) and \( N(1) \). Estimating these objects requires estimates of the causal impact of Medicaid on medical spending and out-of-pocket spending. We once again use the lottery as an instrument for Medicaid to obtain these estimates; Appendix A.1 provides more details. We estimate that Medicaid reduced out-of-pocket spending by $489 and increased medical spending by $885. This yields a total resource cost \( C(1) \) of $1,374 per recipient.

We estimate government costs \( G(1) \) as total medical spending by treatment compliers \( (q = 1) \) of $3,596 (see Table 1); this is broadly consistent with external estimates of the per-recipient spending in the lotteried program in 2001-2004 of about $3,000 (Wallace et al. (2008)[49]). As noted in the Introduction, an estimate of \( G(1) \) is what the Congressional Budget Office would currently use to value Medicaid for recipients (Congressional Budget Office, 2012[45]). As we will see, \( G(1) \) is substantially larger than any of our welfare estimates for Medicaid recipients.

We also estimate substantial transfers to non-recipients of Medicaid, \( N(1) \). We estimate that control compliers \( (q = 0) \) had total medical expenses of $2,711 and out-of-pocket expenses of $489 (see Table 1). Hence, equation (26) indicates that Medicaid delivers a transfer to non-recipients of $2,222.

The bottom panel of Table 3 compares these various cost and transfer measures to our previous estimates of Medicaid’s welfare benefit to recipients, \( \gamma(1) \), from Table 2. In row 3a we estimate the benefit to recipients per dollar of resource costs, i.e., \( \gamma(1)/C(1) \), to be about $1 for the complete-information and the consumption first-order condition approach that proxies for consumption as income minus out-of-pocket spending, and about $0.5 for the consumption first-order condition approach using consumption data and the health first-order condition approach.

Perhaps the most natural benchmark is to compare the value of Medicaid to recipients to the costs to the government (i.e., \( \gamma(1)/G(1) \)). Row 3b shows that Medicaid generates a welfare impact to recipients per dollar of government spending of about $0.4 using the complete-information

---

Medicaid on the budget constraint of non-recipients; Chetty and Saez (2010)[14] provide one modeling structure for this impact. In practice, in the context of the Oregon Health Insurance Experiment, there is no evidence of crowd out of private insurance by Medicaid (Finkelstein et al. (2012)[27]), so we do not examine general equilibrium effects.

In our context, the evidence from the Oregon Health Insurance experiment indicates that only about half the sample had revolving credit, and Medicaid receipt did not affect credit scores (Finkelstein et al., 2012 [27]).
approach or the consumption first-order condition approach based on the consumption proxy, and about $0.2 using the other consumption first-order condition approach or the health first-order condition approach. Recall that we estimate a pure transfer value of Medicaid by the first-order condition approach of $568, or, about $0.2 per dollar of government spending. This can be viewed as a relatively robust lower bound on the value of Medicaid to recipients per dollar of government spending. The key uncertainty is how much value one assigns to the pure-insurance component of Medicaid; as can be seen in Table 2, row 2d, our different approaches yield a wide range of results here.

A striking finding is that Medicaid transfers to non-recipients are large relative to the benefits to recipients. Row 3c shows that we estimate that Medicaid transfers to non-recipients per dollar of government spending (i.e., $N(1)/G(1)) of about $0.6. Depending on which welfare approach is used, transfers to non-recipients are thus between two and three times the size of benefits to recipients. This follows directly from our estimate in the previous section that the uninsured pay only about $0.2 on the dollar for their medical spending, i.e., that about four-fifths of the uninsured’s expenses are paid by external parties. Importantly, our estimate that the uninsured pay relatively little of their medical expenses out of pocket is not an artifact of our setting or of our data. The Kaiser Commission on Medicaid and the Uninsured estimates that the average uninsured person in the U.S. paid $500 out of pocket but incurred total medical expenses of $2443 (Coughlin et al. (2014) [16], Figure 1), suggesting that on average the uninsured in the U.S. pay only 20% of their total medical expenses. To verify this is also true when focusing on low-income populations in the U.S. as a whole, we analyzed out-of-pocket spending using the Medical Expenditure Panel Survey (MEPS) from 2009-2011. We estimate that uninsured adults aged 19-64 below 100 percent of the federal poverty line pay about $0.33 out of pocket for every dollar of their medical expenses. In short, our finding that Medicaid generates substantial transfers to non-recipients is likely to hold in other contexts as well.

Comparing the total benefits of Medicaid - including both those to Medicaid recipients and transfers to non-recipients - to the cost of government spending requires collapsing the estimated impacts on these two parties into one measure. One approach would be to simply sum the two ratios. This suggests total benefits relative to government costs of about $1 for the complete-information and consumption proxy first-order condition approach, and about $0.8 for the other first-order condition approaches. This would be an appropriate measure if the beneficiaries themselves bear the ultimate incidence of the non-recipient transfers. An alternative approach might be to down-weight the social value of transfers to non-recipients to account for the fact that these transfers may accrue to doctors and hospital managers who are at the upper regions of the income distribution. The results in Hendren (2014)[35] suggests a maximum down-weighting of 0.5 to account for the cost of redistributing these transfers from the top of the income distribution to the Medicaid beneficiaries at the bottom of the income distribution. This would suggest that total benefits relative to government costs of about $0.7 for the first two approaches and about $0.5 for the other
two approaches.\footnote{To put these numbers in turn in some context, Hendren (2014)\cite{35} estimates that the EITC generated roughly $0.9 of welfare to EITC recipients for every dollar of government spending. Taking our estimates of 0.5 or 0.7, this suggests that Medicaid is a less efficient method of providing welfare to the bottom of the income distribution than the EITC. However, Medicaid’s benefits accrue more to those who, conditional on income, have higher health expenditures and might therefore be desired (relative to the EITC) if there is a higher social preference for those with higher health expenditures, conditional on income.}

4.4 Sensitivity

Table 4 explores the sensitivity of results within each framework (shown in different rows) to a number of our assumptions (shown in different columns). Column I shows our baseline results for the value of Medicaid to recipients per dollar of government spending $\gamma(1)/G(1)$. Columns II through V explores alternative choices for risk aversion (coefficients of relative risk aversion of 1 and 5, compared to our baseline of 3) and the consumption floor (of $500 or $2,000, compared to our baseline assumption of $1,000). Higher risk aversion or a lower consumption floor increases the value of the program using the complete-information approach or the consumption first-order condition approaches; however the health first-order condition approach is not sensitive to these parameters.\footnote{The health first-order condition approach is mechanically unaffected by our assumption regarding the the coefficient of relative risk aversion because it does not use this parameter. In principle it should likewise not be affected by our assumption regarding the consumption floor. In practice, because - as discussed in Section 3.1 - we implement the consumption floor by adjusting out-of-pocket spending such that the consumption floor holds (i.e. we cap the distribution of out-of-pocket spending at $\bar{y} - c_{floor}$ and because we use the same estimates of of out-of-pocket spending for all approaches, the health first-order condition approach is indirectly (and minimally) affected by our assumption regarding the consumption floor since it affects the estimates of out-of-pocket spending.}

Columns VI through IX explore alternative assumptions regarding the health impact of Medicaid and the value of the health impact. In our baseline estimates, we translated the estimated impact of Medicaid on self-reported health into a mortality improvement using the cross-sectional relationship between self-reported health and mortality. However, the experimental analysis is unable to reject the null hypothesis of no impact of Medicaid on mortality (Finkelstein et al., (2012)\cite{27}) or on specific measures of physical health (Baicker et al. (2013)\cite{6}). In column VI, therefore, we assume no health benefits as a reasonable alternative. In column VII, we retain our baseline measure of the health impact, but assume the value of a statistical life year is $1,750 (as opposed to our baseline assumption of $25,000).\footnote{A VSLY of $1,750 would be appropriate if individuals had utility functions that are separable in health and consumption $u(c,h) = \frac{c^{1-\sigma}}{1-\sigma} + \phi h$ and risk aversion was $\sigma = 3$. Then, a VSLY of $100,000 at the median household income of $50,000 would need to be rescaled by $\left(\frac{50}{13}\right)^3$ to derive the marginal willingness to pay for health for a household earning $13,000, like those in our sample.} In column VIII, we assume a VSLY of $100,000, implicitly assuming no distributional adjustment for the value in Cutler (2004)\cite{19}. Higher health benefits or higher values of health benefits increase the value of the program using the complete-information approach or the health first-order condition approach. However, the consumption first-order condition approach is unaffected because no assumptions regarding health are used.
Column IX uses a depression measure as our health measure, instead of our baseline self-reported health measure. We estimate (see Appendix Table A.1) that Medicaid reduces the probability of screening positive for depression by about 6 percentage points (about 20 percent). The World Health Organization’s calculation of Disability Adjusted Life Years (DALYs) suggests that a moderate depression episode corresponds to a loss of 0.41 life years.\footnote{See Annex Table D, http://www.who.int/healthinfo/statistics/GlobalDALYmethods_2000_2011.pdf} Combining this with the VSLY of \$25K, we assign a value of \$10K to a reduction in depression. For the complete-information approach, using depression instead of subjective health status leads to a smaller estimate of 0.36, as opposed to 0.44 in the baseline specification. This is consistent with depression being not the only health outcome that was affected by Medicaid.\footnote{Adding the subjective health and depression outcomes into the utility function as two separate arguments yields an estimate of 0.47, roughly similar to the baseline estimate of 0.44.} While the complete-information approach requires specifying all elements of the utility function, the health first-order condition approach can be implemented here using just the impact on depression without measurements on the impact on subjective health (this also highlights the versatility of the first-order condition approaches, as they can be implemented using any argument of the utility function, even within health or consumption). Implementing the health first-order condition approach using depression instead of subjective health status, we find an estimate of 0.16, similar to the baseline estimate of 0.19.

The last two columns explore alternative measurement assumptions for key variables. In Column X, we report results using an alternative definition of out-of-pocket spending for those insured by Medicaid. The insured report non-trivial out-of-pocket spending (Finkelstein et al., 2012 [27]).\footnote{Again, this does not appear to be an artifact of our data or setting; in the Medical Expenditure panel survey, Medicaid recipients also self-report substantial out-of-pocket spending (Gross and Notowidigdo (2011) [32]).} In our baseline analysis, we used self reports to measure out-of-pocket spending for the uninsured \((x(0,m))\), but assumed that out-of-pocket spending for the insured followed program rules \((x(1,m) = 0)\) and that therefore any positive self-reported out-of-pocket spending for Medicaid recipients reflected measurement error.\footnote{This is consistent with a model of reporting bias in which individuals are responding to the survey with the general amount of medical spending they incur, 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.} Another possibility, however is that individuals on Medicaid continue to pay for some care out of pocket (either because it is not covered by Medicaid or because providers do not accept Medicaid). Therefore, we report results from an alternative approach in which we assume the self-reported amount of out-of-pocket spending is correct for both the insured and uninsured. We then re-estimate all of our fitted consumption and out-of-pocket spending distributions using a definition of the program with positive values of \(x(1,m)\).\footnote{In constructing \(-\frac{\partial x}{\partial q} = x(0,m(q;\theta)) - x(1,m(q;\theta))\), we assume quantile stability so that we can approximate \(-\frac{\partial x}{\partial q}\) using the difference in out-of-pocket spending quantiles for the given distribution of medical spending, \(m(q,\theta)\), at insurance level \(q\). Further details on the construction of \(-\frac{\partial x}{\partial q}\) when at least some Medicaid recipients have strictly positive out-of-pocket expenditures \((x(1,m) > 0)\) can be found in Appendix A.4.} This, of course, reduces our estimates of \(\gamma(1)\) but also reduces our estimates of \(G(1)\), so that the net effect is a priori ambiguous; in practice, Column X shows that it lowers our estimates of \(\gamma(1)/G(1)\).
In Column XI we consider an alternative assumption about average income \( \bar{y} \) in computing consumption in equation (17). Our baseline approach used average per capita self-reported income of compliers for \( \bar{y} \); this resulted in average per capita consumption for control compliers of $3,320, considerable below the $13,541 estimate of non-medical per-capita consumption for uninsured adults below the federal poverty line in the CEX. To examine the sensitivity of our results to alternative assumptions about average consumption, we report results assuming that \( \bar{y} \) is $14,030, which is the sum of mean non-medical consumption in the CEX ($13,541) plus out-of-pocket spending of control compliers in the Oregon sample ($489). We raise the consumption floor by the same proportion as we raised average income, yielding a consumption floor of $3,704; this value is about the 1st percentile of reported consumption for our uninsured sample in the CEX. As seen in Column XI, under these alternative assumptions, the value of Medicaid to recipients based on either the complete-information approach or the consumption first-order condition approach using consumption proxy increases substantially; the results from the other two approaches are barely affected.\(^{48}\)

The somewhat counter-intuitive result that the value of insurance increases with average consumption comes from the presence of a consumption floor; as a result of the floor, increases in average consumption increase exposure to downside risk and hence the value of insurance.

Looking across the columns gives a sense of the scope and drivers of our estimates. Under the complete-information approach and the consumption first-order condition approach using the consumption proxy, the value of Medicaid to recipients per dollar of government spending gets as high as $0.83 (respectively, 0.86) - by using an average income level based on average consumption reported in the CEX rather than based on self-reported income (column XI) - and as low as $0.29 (respectively, 0.22) - by relaxing the assumption that those on Medicaid pay nothing out of pocket (column X). These same alternative specifications generate the highest and lowest estimates under the consumption first-order condition approach based on the direct consumption measure, but the results vary very little (from $0.15 to $0.22). Under the health first-order condition approach, the welfare estimates get as high as $0.28 - by assuming substantially larger health benefits (column VIII) - and as low as $0.14 - by relaxing the assumption that those on Medicaid pay nothing out of pocket (column IX).

### 4.5 Discussion of Different Approaches

The health first-order condition approach and the consumption first-order condition approach based on consumption data consistently deliver lower point estimates of welfare gains per dollar of government spending than the consumption first-order condition approach based on the consumption

\(^{48}\)Again, in principle, the estimates from the health first-order condition approach and the consumption first-order approach based on the direct consumption measure should not be affected by this alternative assumption regarding \( \bar{y} \). In practice, the estimates from these other two approaches are affected because we implement the consumption floor (used in the complete-information and consumption first-order condition approach with the consumption proxy) by capping the distribution of out-of-pocket spending at \( \bar{y} - c_{floor} \) and, for consistency, we use the same distribution of out-of-pocket spending for all approaches (even ones that do not depend on consumption). In addition, the change in the assumed consumption floor can affect the consumption first-order condition approach using the direct consumption measure.
proxy or the complete-information approach, both of which tend to produce similar estimates. Which approach one wants to rely on depends on which of the various assumptions each requires one is most comfortable with.

We are least confident in the results from the health first-order condition approach; the difficulties in estimating heterogeneity in health returns to out-of-pocket spending create considerably uncertainty around the results, as reflected by the much wider confidence intervals from this approach than from the others (see, e.g., Table 2). In addition, our implementation of the health first-order condition approach may produce downward biased estimates of $\gamma(1)$ because (as noted in Section 4.2) our estimation of the health returns to out-of-pocket spending conditional on $\theta^K$ misses any within-$\theta^K$ insurance and (as noted in Section 2.2.3) may be downward biased for individuals at a corner solution with respect to medical spending; about 20 percent of treatment compliers and 30 percent of control compliers are at the corner of zero medical spending (suggesting this may be a non-trivial issue).

On the other hand, our consumption-based estimates of may be biased upward. The consumption proxy measure (used in the complete-information approach and in one variant of the consumption first-order condition approach) models consumption as income minus out-of-pocket expenses and therefore ignores the possibility of the uninsured smoothing consumption through other means such as savings, borrowing, or transfers from friends or family. Our direct consumption measure in the CEX (used in our other variant of the consumption first-order condition approach) shows a negative covariance between marginal utility of consumption and out-of-pocket medical expenditures among the uninsured in the raw (unadjusted) data, suggesting that Medicaid transfers resources to states of the world with lower marginal utilities of consumption; the estimates of $\gamma(1)$ that we report use a measurement-error correction to produce a positive “pure-insurance term” in this approach.

There are countless other comparisons one could make across the different approaches. We mention a few of them briefly here. First, we estimate a price of medical care of 0.2 among the uninsured in our sample, i.e., that, on average, the uninsured pay a fifth of the cost of their medical care out of pocket. Our first-order condition approaches assume this price is constant and the same for all medical treatments. However, if the uninsured face a range of prices and are more likely to undergo treatments with a low price, then our estimate of the price will be biased down because it based on the selected sample of treatments undergone. A downward bias in the price reduces the estimate of the transfer term (via equation (23)) of the first-order condition approaches, thus reducing the estimate of $\gamma(1)$.49 Similarly, as discussed in Section 2.2.4, the linear interpolation that we use for the first-order condition approaches may cause us to miss part of the value of Medicaid to recipients coming from its liquidity effects. However, the complete-information approach would not be affected by either of these two potential biases because it does not require estimates of the price and it does not rely on linear interpolation.

Since the complete-information approach requires specifying all arguments of the utility function

---

49 This bias can be bounded. In the extreme case that the uninsured face a true price of one, the transfer term would become $932 (=489+885/2$, see equation (23)) as opposed to our baseline estimate of $568$. 

32
while the first-order condition approaches do not, one could view our estimates from this approach as a likely lower bound of $\gamma(1)$ because they do not capture welfare benefits for other utility-relevant outcomes (e.g., marital stability or welfare of children) that may be affected by the program but are not specified in the complete-information analysis. The fact that the welfare estimates from the complete-information approach tend to be the highest of the approaches might be interpreted as indicating that there are no important omitted arguments to the utility function affected by Medicaid. Moreover, if one believes our modeling structure and implementation assumptions in the first-order condition approaches are sound, the fact that the consumption first-order condition approach based on the consumption proxy generates substantially different results from the health first-order condition approach could be interpreted as a rejection of optimizing behavior by recipients. In this case, one may prefer the complete-information welfare estimate, which does not require an assumption of optimization.

Finally, as emphasized in equation (19) above, estimation of the transfer component of the first-order condition does not require any specification of the utility function. As a result, we view the $568$ estimate of this transfer component as a relatively robust lower bound on the value of Medicaid, i.e., one that values Medicaid to recipients as a pure transfer and ignores any potential insurance benefits.

5 Conclusion

Welfare estimation of non-market goods is important, but also challenging. As a result of these challenges, the welfare benefits from Medicaid are often ignored in academic and public policy discourse, or based on ad-hoc approaches.

In this paper, we have developed, implemented, and compared the results from alternative formal frameworks for valuing a Medicaid expansion that occurred by random assignment in Oregon. Our baseline estimates indicate a welfare benefit to recipients per dollar of government spending of roughly between $0.2$ and $0.4$, depending on the framework used. Ignoring the insurance value of Medicaid, the transfer Medicaid provides to recipients indicates a lower bound on its welfare benefit to recipients of about $0.2$ per dollar of government spending.

As we have emphasized throughout, the welfare estimates are naturally affected by a variety of modeling, calibration, and data choices. We have endeavored to explore sensitivity on each of these dimensions. Across a variety of alternative specifications, we consistently find that Medicaid’s value to recipients is lower than the government’s costs of the program, and usually substantially below. This stands in contrast to the current approach used by the Congressional Budget Office to value Medicaid at its cost. It is, however, not inconsistent with the few other attempts we know of to formally estimate a value for Medicaid; these are based on using choices to reveal ex-ante

---

50 We consider it a “likely” lower bound because we cannot rule out that Medicaid has a negative impact on some other utility relevant outcomes. For example, if Medicaid induces someone to increase labor supply, we might not measure the reduction in utility from leisure. In practice, the Oregon Health Insurance Experiment found no impact of Medicaid on employment.
willingness to pay, and tend to find estimates (albeit for different populations) in the range of 0.3 to 0.5.\footnote{Researchers have attempted to elicit willingness to pay for Medicaid in other contexts through quasi-experimental variation in premiums (Dague (2014)[21]), and the extent to which individuals distort their labor earnings in order to become eligible for Medicaid (Gallen 2014 [28], Keane and Moffitt (1995) [37]). These approaches - which face their own challenges - are not available in the context of the Oregon Health Insurance Experiment, since it randomized the ability to apply for Medicaid but not the premium at which one could do so or the eligibility requirements.}

We also find that Medicaid delivers a substantial transfer to non-recipients of about $0.6 per dollar of government spending – larger than our baseline estimates of the value of Medicaid to the recipients. This large transfer to non-recipients stems directly from our estimate that the uninsured pay only a small fraction of medical expenditures; we confirmed that this holds not only in our context but more generally in national survey data as well. It is also consistent with recent findings of Garthwaite, Gross, and Notowidigdo (2015 [30]) who find that Medicaid significantly reduces the provision of uncompensated care by hospitals. This points to the importance of further work to determine who bears both the immediate and ultimate economic incidence of these large Medicaid transfers to non-recipients.

While we tailored our frameworks to our application, they offer insights for future welfare analysis of other public health insurance programs. Natural applications would be to consider the value of Medicaid over longer horizons than the first year of coverage studied here, or for other Medicaid recipients than able-bodied adults; there is a rich empirical literature examining the impact of Medicaid on outcomes for the other covered populations\footnote{see Gruber (2003)[33] and Buchmueller et al. (in progress)[10] for reviews.} - children, the disabled, and the elderly - to which the approaches developed here may be relatively straightforwardly applied to produce welfare estimates. Likewise, our frameworks could be applied to the empirical literature examining the impacts of Medicare on health care use, health, and out-of-pocket medical expenditures (e.g., Card et al. (2008, 2009)[11, 12], Barcellos and Jacobson (forthcoming)[8]).

Our development of the first-order condition approach also highlighted the importance for welfare analysis of a set of empirical constructs that have received very little attention to date in empirical analysis of health insurance: namely the covariance between the change in out-of-pocket spending induced by insurance (at a given level of medical spending) and the marginal utility of medical spending (via its marginal effect on health) or the marginal utility of consumption. The ability to value financial assets using covariances is a well-known result from both the optimal-taxation literature and the asset-pricing literature. Yet, we believe its application in the context of health insurance, with its representation in terms of either consumption or health, is novel and suggests a fruitful direction for further empirical work. We highlighted some of the challenges in measuring each covariance. Empirical progress on estimating these relationships is an important area for further work.

More generally, our results illustrate the possibilities but also the difficulties in doing welfare analysis even with a rich set of causal effects of the program. 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, rather than the common defaults of zero valuation or valuation at 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


Figure 1: From $\frac{dy}{dq}(q)$ to $\gamma(1)$

Figure 2: Consumption Distribution for Treatment and Control Compliers
<table>
<thead>
<tr>
<th></th>
<th>I</th>
<th>II (q=1)</th>
<th>III (q=0)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Full Sample</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Panel A: Oregon Data Demographics</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>0.60</td>
<td>0.57</td>
<td>0.60</td>
</tr>
<tr>
<td>Age 50-64</td>
<td>0.34</td>
<td>0.36</td>
<td>0.35</td>
</tr>
<tr>
<td>Age 19-49</td>
<td>0.66</td>
<td>0.64</td>
<td>0.65</td>
</tr>
<tr>
<td>Share White</td>
<td>0.83</td>
<td>0.84</td>
<td>0.84</td>
</tr>
<tr>
<td>Share Black</td>
<td>0.03</td>
<td>0.03</td>
<td>0.03</td>
</tr>
<tr>
<td>Share Spanish / Hispanic / Latino</td>
<td>0.11</td>
<td>0.08</td>
<td>0.08</td>
</tr>
<tr>
<td><strong>Panel B: Oregon Data Outcomes</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Medical spending ($m$)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean medical spending, $E[m]$</td>
<td>2990</td>
<td>3596</td>
<td>2711</td>
</tr>
<tr>
<td>Fraction with positive medical spending, $E[m &gt; 0]$</td>
<td>0.74</td>
<td>0.79</td>
<td>0.72</td>
</tr>
<tr>
<td>Out-of-pocket spending ($x$)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean out-of-pocket spending, $E[x]$</td>
<td>351</td>
<td>0</td>
<td>481</td>
</tr>
<tr>
<td>Fraction with positive out-of-pocket spending, $E[x &gt; 0]$</td>
<td>0.38</td>
<td>0</td>
<td>0.56</td>
</tr>
<tr>
<td>Fraction in good, very good or excellent health, $E[h]$</td>
<td>0.59</td>
<td>0.61</td>
<td>0.47</td>
</tr>
</tbody>
</table>

Notes: 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, based on using the lottery as an instrument for Medicaid coverage (See Appendix A.1 for details on how population means are calculated for treatment and control compliers). See text for detailed definitions of variable construction in Panel B. Spending and consumption are expressed in dollars per year per person.
### Table 2: Welfare Benefit Per Recipient

<table>
<thead>
<tr>
<th></th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>First-order condition (FOC) Approaches</td>
<td>Complete-Information Approach</td>
<td>Consumption (Consumption Proxy)</td>
<td>Consumption (CEX Consumption Measure)</td>
</tr>
<tr>
<td>1. Welfare Effect on Recipients, $\gamma(1)$</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1576</td>
<td>1247</td>
<td>694</td>
<td>680</td>
</tr>
<tr>
<td></td>
<td>(116)</td>
<td>(367)</td>
<td>(422)</td>
<td>(2991)</td>
</tr>
<tr>
<td>2. Decomposition of Welfare Effect on Recipients</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2a. Welfare gain operating through consumption</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>1111</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2b. Welfare gain operating through health</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>465</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2c. Transfer component</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Operating through consumption</td>
<td>693</td>
<td>568</td>
<td>568</td>
<td>568</td>
</tr>
<tr>
<td>Operating through health</td>
<td>489</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>205</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>2d. Pure-Insurance (non-transfer) component</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Operating through consumption</td>
<td>883</td>
<td>678</td>
<td>126</td>
<td>112</td>
</tr>
<tr>
<td>Operating through health</td>
<td>622</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>260</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: All estimates are expressed in dollars per year per Medicaid recipient. Row 1 presents estimates of the welfare impact on recipients, $\gamma(1)$, for each of the approaches. Row 2 decomposes this number into components using equation (16) for the complete-information approach, equation (13) for the consumption first-order condition approach, and equation (14) for the health first-order condition approach. The sample in column III is limited to single individuals. Standard errors are calculated based on bootstrapping with 500 repetitions.
### Table 3: Costs and Benefit-Cost Ratios

<table>
<thead>
<tr>
<th></th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>First-order condition (FOC) Approaches</strong></td>
<td>Complete-Information Approach</td>
<td>Consumption (Consumption Proxy)</td>
<td>Consumption (CEX Consumption Measure)</td>
<td>Health</td>
</tr>
<tr>
<td><strong>1. External Transfers and Costs</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>1a. Resource Costs, C(1)</td>
<td>1374</td>
<td>1374</td>
<td>1374</td>
<td>1374</td>
</tr>
<tr>
<td>(standard error)</td>
<td>(254)</td>
<td>(254)</td>
<td>(254)</td>
<td>(254)</td>
</tr>
<tr>
<td>Impact on Medical Spending</td>
<td>885</td>
<td>885</td>
<td>885</td>
<td>885</td>
</tr>
<tr>
<td>1b. Government Costs, G(1)</td>
<td>3596</td>
<td>3596</td>
<td>3596</td>
<td>3596</td>
</tr>
<tr>
<td>1c. Transfers to external parties, N(1)</td>
<td>2222</td>
<td>2222</td>
<td>2222</td>
<td>2222</td>
</tr>
<tr>
<td><strong>2. Welfare Benefit per Recipient, γ(1)</strong></td>
<td>1576</td>
<td>1247</td>
<td>694</td>
<td>680</td>
</tr>
<tr>
<td><strong>3. Benefit-cost ratios</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>3a. γ(1) / C(1)</td>
<td>1.15</td>
<td>0.91</td>
<td>0.51</td>
<td>0.49</td>
</tr>
<tr>
<td>(standard error)</td>
<td>(0.25)</td>
<td>(0.29)</td>
<td>(0.32)</td>
<td>(2.62)</td>
</tr>
<tr>
<td>3b. γ(1) / G(1)</td>
<td>0.44</td>
<td>0.35</td>
<td>0.19</td>
<td>0.19</td>
</tr>
<tr>
<td>(standard error)</td>
<td>(0.04)</td>
<td>(0.10)</td>
<td>(0.12)</td>
<td>(0.86)</td>
</tr>
<tr>
<td>3c. N(1) / G(1)</td>
<td>0.62</td>
<td>0.62</td>
<td>0.62</td>
<td>0.62</td>
</tr>
<tr>
<td>(standard error)</td>
<td>(0.06)</td>
<td>(0.06)</td>
<td>(0.06)</td>
<td>(0.06)</td>
</tr>
</tbody>
</table>

Notes: All transfers, costs, and welfare estimates are expressed in dollars per year per Medicaid recipient. Row 1 presents estimates of the external transfers and costs of Medicaid, as outlined in equations (25)-(27). Row 2 repeats the baseline estimates for each approach from Table 1. Row 3 computes benefit-cost ratios: Row 3a shows the welfare impact on recipients per dollar of resource costs; Row 3b shows the welfare impact on recipients per dollar of government spending; Row 3c shows the net transfers to external parties per dollar of government expenditures. The sample in column III is limited to single individuals. Standard errors are calculated based on bootstrapping with 500 repetitions.
Table 4: Sensitivity of Welfare Estimates to Assumptions

<table>
<thead>
<tr>
<th></th>
<th>Baseline</th>
<th>Sensitivity to CRRA</th>
<th>Sensitivity to consumption floor</th>
<th>Sensitivity to VSLY</th>
<th>Sensitivity to measure of health</th>
<th>Sensitivity to OOP spending at q=1</th>
<th>Sensitivity to mean income</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \gamma(1) / G(1) )</td>
<td>Complete-Information Approach</td>
<td>0.44 0.41 0.49</td>
<td>0.52 0.37 0.31 0.32 0.61</td>
<td>0.36 0.29 0.83</td>
<td>Consumption FOC Approach (Consumption Proxy)</td>
<td>0.35 0.22 0.43 0.47 0.20 0.35 0.35 0.35 0.35 0.22 0.86</td>
<td>Consumption FOC Approach (Direct Consumption Measure)</td>
</tr>
</tbody>
</table>

**Assumptions**

**Relevant for complete-information and consumption FOC approaches**

- Coefficient of relative risk aversion (CRRA)
  - 3 1 5 3 3 3 3 3 3 3 3
- Consumption floor (in $ per capita per year)
  - 1000 1000 1000 500 2000 1000 1000 1000 1000 1000 3704
- Mean income (in $ per capita per year)
  - 3808 3808 3808 3808 3808 3808 3808 3808 3808 3808 14030

**Relevant for complete-information and health FOC approaches**

- Value of a Statistical Life Year (VSLY, in $)
  - 25,000 25,000 25,000 25,000 25,000 0 1,750 100,000 N/A 25,000 25,000

**Relevant for all approaches**

- Out-of-pocket spending for treatment compliers
  - 0 0 0 0 0 0 0 0 0 Data 0

**Notes:** All benefit-to-cost estimates are expressed in dollars per year per Medicaid recipient. This table presents the sensitivity of the baseline estimates in Table 2 to alternative assumptions and specifications. Columns II-III adjust the coefficient of relative risk aversion from 1 to 5, as compared to our baseline parameter of 3. Columns IV-V adjust the consumption floor between 500 and 2000, as opposed to our baseline parameter of 1000. Columns VI-VIII set the value of a statistical life year at 0, $1,750 or $100,000, as compared to our baseline value of $25,000. The estimate for the health first-order condition approach in column VI is based on the limit when the VSLY approaches zero. Column IX uses the reduction in depression symptoms to value health improvements. Column X reports results from a specification that drops the assumption that individuals have zero out-of-pocket spending under Medicaid but instead treats self-reported out-of-pocket medical spending as the estimate of out-of-pocket health spending under Medicaid. Column XI reports results in which mean income is set at $14,030, as compared to our baseline value of $3808. In Column XI, mean income is set equal to the sum of mean out-of-pocket medical spending of Oregon control compliers ($489) and mean reported non-health consumption among uninsured individuals in baseline CEX sample ($13,541). We set the consumption floor at $3,704, which ensures that the consumption floor is the same fraction of mean income in Column XI as in our baseline specification. The sample for the consumption first-order condition approach using the direct consumption measure is limited to single individuals.
A Online Appendices

A.1 Instrumental variable analysis of the Oregon Health Insurance Experiment data

Our application uses the Oregon Medicaid lottery and data previously analyzed by Finkelstein et al. (2012) [27] and publicly available at www.nber.org/oregon. This section provides some additional information on how we analyze the data. Much more details on the data and the lottery can be found in Finkelstein et al. (2012) [27].

A.1.1 Estimation of mean impacts

When analyzing the mean impact of Medicaid on an individual outcome \( y_i \) (such as medical spending \( m_i \), out-of-pocket spending \( x_i \), or health \( h_i \)), we estimate equations of the following form:

\[
y_i = \alpha_0 + \alpha_1 \text{Medicaid}_i + \epsilon_i,
\]

where \( \text{Medicaid}_i \) is an indicator variable for whether the individual is covered by Medicaid at any point in the study period. We estimate equation (27) by two-stage least squares, using the following first-stage equation:

\[
\text{Medicaid}_i = \beta_0 + \beta_1 \text{Lottery}_i + \nu_i,
\]

in which the excluded instrument is the variable “Lottery” which is an indicator variable for whether the individual was selected by the lottery.

One particular feature of the lottery design affects our implementation. The lottery selected individuals, but if an individual was selected, any household member could apply for Medicaid. As a result, if more people from a household were on the waiting list, the household had more “lottery tickets” and a higher chance of being selected. The lottery was thus random conditional on the number of people in the household who were on the waiting list, which we refer to as the number of “lottery tickets.” In practice, about 60 percent of the individuals on the list were in households with one ticket, and virtually all the remainder had two tickets. (We drop the less than 0.5 percent who had three tickets; no one had more). In households with two tickets, the variable “lottery” is one if any household member was selected by the lottery. In all of our analysis, therefore, we perform the estimation separately for one-ticket and two-ticket households. Because there is no natural or interesting distinction between these two sets of households, all estimates presented in the paper consist of the weighted average of the estimates of these two groups.

Much of our analysis is based on estimates of characteristics of treatment and/or control compliers - i.e., those who are covered by Medicaid if and only if they win the lottery (see, e.g., Angrist and Pischke (2009) [2]). Our estimation of these characteristics is standard. For example, uninsured individuals who won the lottery provide estimates of characteristics of never-takers. Since uninsured individuals who lost the lottery include both control compliers and never-takers, with
estimates of the never-taker sample and the share of individuals who are compliers, we can back out the characteristics of control compliers. Likewise, insured individuals who lost the lottery provide estimates of characteristics of always-takers. Since insured lottery winners include both treatment compliers and always-takers, we can in like manner identify the characteristics of treatment compliers. Differences between treatment and control compliers reflect the impact of Medicaid (i.e., $\alpha_1$) in the IV estimation of equation (27).

To make this more concrete, let $f_g(x)$ denote the distribution of $x$ for group $g \in \{TC, CC, AT, NT\}$ where $TC$ are the treatment compliers, $CC$ are the control compliers, $AT$ are the always-takers, and $NT$ are the never-takers. We observe, $f_{NT}(x)$, the distribution of $x$ for the never-takers, as the distribution of $x$ for those who choose not to take up in the treatment group. The population fraction of never-takers, $\pi_{NT}$, is given by the fraction of the treatment group that did not take up the program. Similarly, $f_{AT}(x)$, the distribution of $x$ for the always-takers, is given by the observed distribution of $x$ for those who choose to take up in the control group, and the population fraction of always-takers, $\pi_{AT}$, is given by the fraction of the control group that took up the program. The population fraction of compliers is given by: $\pi_C = 1 - \pi_{NT} - \pi_{AT}$. However, the distribution of $x$ for compliers requires more work and differs for compliers in the control group and those in the treatment group. In the control group, those choosing not to take up are a mixture of never-takers and control compliers (those who would take up if offered). Using the observed distribution of $x$ for never-takers (see above), we can back out $f_{CC}(x)$, the distribution of $x$ for the compliers in the control group, by noting that the distribution of $x$ for the those who don’t take up the program in the control group is given by: $\frac{\pi_C}{\pi_C + \pi_{NT}} f_{CC}(x) + \frac{\pi_{NT}}{\pi_C + \pi_{NT}} f_{NT}(x)$. Similarly, those who take up the program in the treatment group are a mixture of always-takers and treatment compliers. Using the observed distribution of $x$ for always-takers (see above), we can back out $f_{TC}(x)$, the distribution of $x$ for the compliers in the treatment group, by noting that the distribution of $x$ for those who take up the program in the treatment group is given by: $\frac{\pi_C}{\pi_C + \pi_{AT}} f_{TC}(x) + \frac{\pi_{AT}}{\pi_C + \pi_{AT}} f_{AT}(x)$. So, for example, one can solve for the treatment complier mean, $\mu_{TC}$, using the equation $\frac{\pi_C}{\pi_C + \pi_{AT}} \mu_{TC} + \frac{\pi_{AT}}{\pi_C + \pi_{AT}} \mu_{AT} = \mu_{TT}$, where $\mu_{TT}$ is the observed mean of $x$ of those in the treatment group who take up the program and $\mu_{AT}$ is the observed mean of those who take up the program in the control group. This yields:

$$\mu_{TC} = \frac{(\pi_C + \pi_{AT}) \mu_{TT} - \pi_{AT} \mu_{AT}}{\pi_C}.$$  

Similarly, the formula for control complier means is given by:

$$\mu_{CC} = \frac{(\pi_C + \pi_{NT}) \mu_{CN} - \pi_{NT} \mu_{NT}}{\pi_C},$$

where $\mu_{CN}$ denotes the observed mean of $x$ among those in the control group who do not take up the program. These formulas were used to compute the the complier means presented in the text.
A.1.2 Estimation of impact on out-of-pocket spending distribution

To estimate the distribution of out-of-pocket spending for the treatment and control compliers in our relatively small sample, we follow a parametric IV technique. Fortunately, reported out-of-pocket spending follows very nicely a log-normal distribution combined with a mass at zero spending. Therefore, we approximate the distribution of out-of-pocket spending by assuming that out-of-pocket spending is a mixture of a mass point at zero and a log-normal spending distribution for positive values. We allow the parameters of this mixture distribution to differ across four groups: treatment compliers (TC), control compliers (CC), always-takers (AT), and never-takers (NT). Specifically, let $F^g_x$ denote the CDF of out-of-pocket spending for group $g$:

$$F^g_x(\phi^g, \mu^g, \nu^g) = \phi^g + (1 - \phi^g) \text{LOGN}(x|\mu^g, \nu^g) \quad \text{for } g \in \{TC, CC, AT, NT\}$$

where $\text{LOGN}(x|\mu, \nu)$ is the CDF of a lognormal distribution with mean and variance parameters, $\mu$ and $\nu$, evaluated at $x > 0$. For $x = 0$, the CDF is given solely by $\phi^g$, so that this parameter captures the fraction of group $g$ with zero out-of-pocket spending. Under standard IV assumptions, the 12 parameters are identified from the joint distribution of out-of-pocket spending, insurance status, and lottery status. (In practice, we estimate $F^g$ separately for households with 1 and 2 lottery tickets, and therefore estimate 12 parameters).

In particular, we fit the mixture distribution for never-takers to the observed out-of-pocket spending distribution of uninsured individuals who won the lottery. The distribution of out-of-pocket spending for uninsured lottery losers is a mixture of the distribution for never-takers and control compliers; thus, with the parameters for never-takers already identified, the distribution for uninsured lottery losers allows us to identify the parameters of the distribution for control compliers. Similarly, the distribution of out-of-pocket spending among insured lottery losers identifies the parameters for always-takers. The distribution of out-of-pocket spending among the insured lottery winners is a mixture of the distribution for always-takers and treatment compliers; thus we can in like manner identify the parameters for treatment compliers. Except for the specification in column X of Table 4, we set the distribution of out-of-pocket expenditures to zero for treatment compliers because Medicaid does not require copayments and charges zero or negligible premiums. We estimate all parameters jointly using maximum likelihood.

To assess the goodness of fit, Figure A1 plots the estimated and actual CDF separately based on lottery status (won or lost), insurance status, and number of tickets. As can be seen from these figures, the parametric model fits quite well.

53To ensure consistency with the consumption floor and to ensure that the relationship $x + c = \bar{y}$ always holds for the uninsured in our data, we redefine out-of-pocket spending $x$ as $\min(x', \bar{y} - c)$ where $x'$ is fitted out-of-pocket spending in the model. For the insured, out-of-pocket spending is always consistent with the consumption floor because we have imposed $x(1,m) = 0$. 

46
A.1.3 Results and comparison to previous results

Our sample, variable definitions, and estimation approach are slightly different from those in Finkelstein et al. (2012) [27]. Table A.1 walks through the differences in the approaches and shows that these differences are fairly inconsequential for the estimates reported in the two papers. Column 1 replicates the results from Finkelstein et al. (2012)[27]. In column 2, we limit the data to the subsample used in our own analysis, which consists of about 15,500 individuals out of the approximately 24,000 individuals from Finkelstein et al. (2012)[27]. Our subsample excludes those who have missing values for any the variables we use in the analysis. The primary reason for the loss of sample size is missing information on prescription drug utilization (a component of medical spending). Missing data on self-reported health, household income, number of family members, out-of-pocket spending, and other health care use also contribute slightly to the reduction of sample size. We also exclude the few people who had three people in the household signed up for the lottery, as described above.

Column 3 reports the results on our subsample using our estimating equations above. These estimating equations differ from those Finkelstein et al. (2012) [27] in several ways. First, we stratify on the number of tickets and report weighted averages of the results rather than include indicator variables for the number of tickets, as in Finkelstein et al. (2012) [27]; we thus allow the effects of insurance to potentially differ by number of tickets. Second, we do not control for which of the 8 different survey waves the data come from as in Finkelstein et al. (2012) [27]. And finally, we do not up-weight the subsample of individuals in the intensive-follow-up survey arm. As shown in column 3, these deviations do not meaningfully affect the results.

Finally, column 4 reports the results using our subsample and our estimating equation, adjusting the “raw” out-of-pocket data as described in Section 3.1. Specifically, we estimate the distribution of out-of-pocket by fitting the distribution described above, set out of pocket spending to zero for the insured, and impose a ceiling on out-of-pocket spending for the uninsured. Naturally, these adjustments only affect the estimated effect of Medicaid on out-of-pocket spending.

A.2 Decomposition of welfare effects in the complete-information approach

A.2.1 Marginal decomposition

As in the first-order condition approaches, we can decompose the marginal welfare impact on the recipient in the complete-information approach into transfer and insurance terms. Given that Medicaid affects the allocation of $c$ and $m$ across states of the world, we rewrite equation (16) in terms of $c$ and $m$ by using equation (8):

---

54 Covariates are more difficult to handle in our estimates of the distributional impact of Medicaid on out-of-pocket spending (and, hence, consumption), so we stratify by ticket size in the analyses of effects on distributions. We do the same thing for our mean estimates for consistency.

55 Starting from the raw data in column III, imposing the fitted distribution has very little effect (the estimated impact of Medicaid on out-of-pocket spending changes from -$346 to -$349; imposing that the insured have zero out of pocket spending raises this estimate to -$564, and from there the imposition of the cap on out of pocket spending of $\bar{y} - c_{floor}$ reduces the estimate to $489$, given our baseline consumption floor of $1,000$. 

---
\[
\frac{d\gamma(q)}{dq} = E \left[ \frac{u_c}{E[u_c]} \frac{dc}{dq} \right] + E \left[ \frac{u_h}{E[u_c]} \frac{dh}{dm} \frac{dm}{dq} \right].
\]

We condition on \( m \) in the last term in order to allow for the possibility that there is remaining uncertainty over the state of the world \( \theta \) after medical spending \( m \) has been chosen. The consumption and health terms can each be decomposed into a transfer term and a pure insurance term:

\[
\frac{d\gamma(q)}{dq} = E \left[ \frac{u_c}{E[u_c]} \frac{dc}{dq} \right] + E \left[ \frac{u_h}{E[u_c]} \frac{dh}{dm} \frac{dm}{dq} \right].
\]

Equation (29) shows that the value of insurance under the complete-information approach results both from the mean increase in consumption, \( E \left[ \frac{dc}{dq} \right] \), and medical spending, \( E \left[ \frac{dm}{dq} \right] \), and also their insurance values from moving consumption and medical spending to states of the world with higher marginal utilities, as measured by the latter two covariances. In contrast to the first-order condition approaches, the individual may value an additional unit of consumption more or less than an additional unit of out-of-pocket medical spending; hence, the transfer and insurance values cannot be represented using terms only involving the marginal utility of consumption or the marginal utility of health.

### A.2.2 Non-marginal implementation

In practice, since we estimate non-marginal changes in welfare directly in the complete-information approach through equation (18), we conduct the welfare decomposition directly off the non-marginal estimate. Specifically, we decompose the welfare effect that we estimated in equation (18) as \( \gamma(1) = \gamma_C + \gamma_M \), where \( \gamma_C \) denotes the welfare component associated with the effects of the program on consumption and \( \gamma_M \) the component due to changes in health. By substituting the health production function (equation (2)) into the definition for \( \gamma \) (equation (3)), we obtain an implicit expression for \( \gamma_C + \gamma_M \) that is in terms of consumption and health:

\[
E \left[ u \left( c(0; \theta), \tilde{h}(m(0, \theta); \theta) \right) \right] = E \left[ u \left( c(1; \theta) - \gamma_C - \gamma_M, \tilde{h}(m(1, \theta); \theta) \right) \right].
\]

Given the additive separability of the utility function, we can estimate \( \gamma_C \) just based on the consumption term in the utility function:
\[
E \left[ \frac{c(0; \theta)^{1-\sigma}}{1-\sigma} \right] = E \left[ \frac{(c(1; \theta) C)^{1-\sigma}}{1-\sigma} \right],
\]
and calculate \( \gamma_M \) from our estimates of \( \gamma(1) \) and \( \gamma_C \) using the identity:

\[
\gamma_M = \gamma(1) - \gamma_C.
\]

Of course, due to the curvature of the utility function, the order of operations can matter.

We can further decompose the welfare components associated with consumption effects (\( \gamma_C \)) and effects on health (\( \gamma_M \)) into a transfer and a pure-insurance component. We estimate the consumption transfer term (\( \gamma_{C,\text{Transfer}} \)) as the mean increase in consumption due to the program so that

\[
\gamma_{C,\text{Transfer}} = E[c(1; \theta) - c(0; \theta)].
\]

The pure-insurance component operating through consumption (\( \gamma_{C,\text{Ins}} \)) is then:

\[
\gamma_{C,\text{Ins}} = \gamma_C - \gamma_{C,\text{Transfer}}.
\]

We can similarly decompose the welfare components due to effects on health (\( \gamma_M \)) into a transfer component (\( \gamma_{M,\text{Transfer}} \)) and an insurance component (\( \gamma_{M,\text{Ins}} \)). We estimate the transfer component in health (\( \gamma_{M,\text{Transfer}} \)) by:

\[
E \left[ \frac{c(0; \theta)^{1-\sigma}}{1-\sigma} + \tilde{\phi} \tilde{h} (E[m(0, \theta)]; \theta) \right] = E \left[ \frac{(c(1; \theta) - \gamma_C - \gamma_{M,\text{Transfer}})^{1-\sigma}}{1-\sigma} + \tilde{\phi} \tilde{h} (E[m(1, \theta)]; \theta) \right]
\]
so that \( \gamma_{M,\text{Transfer}} \) is the additional welfare benefit for the health improvements that would come with an average increase in medical spending due to the program. Approximating this health improvement by \( E \left[ \frac{d\tilde{h}}{dm} \right] E \left[ m(1, \theta) - m(0, \theta) \right] \), we implement this calculation of \( \gamma_{M,\text{Transfer}} \) as the solution to:

\[
E \left[ \frac{c(0; \theta)^{1-\sigma}}{1-\sigma} - (c(1; \theta) - \gamma_C - \gamma_{M,\text{Transfer}})^{1-\sigma} \right] = \tilde{\phi} E \left[ \tilde{h}(E[m(1, \theta)]; \theta) - \tilde{h}(E[m(0, \theta)]; \theta) \right] = \tilde{\phi} E \left[ \frac{d\tilde{h}}{dm} \right] E \left[ m(1, \theta) - m(0, \theta) \right].
\]

This requires an estimate of \( E \left[ \frac{d\tilde{h}}{dm} \right] \), the slope of the health production function between \( m(1, \theta) \) and \( m(0, \theta) \), averaged over all states of the world. We estimate \( \frac{d\tilde{h}}{dm} \) using an approach described in Section 4.2 above, and then take its expectation here. Finally, the pure-insurance component operating through health (\( \gamma_{M,\text{Ins}} \)) is given by:

\[
\gamma_{M,\text{Ins}} = \gamma_M - \gamma_{M,\text{Transfer}}.
\]
A.3 Health production function, $E_{\theta|\theta^K} \left[ \frac{\partial h}{\partial m} \right]$

To implement the health first-order condition approach, we must estimate the health returns to medical spending conditional on medical spending, $m$. To do so, we use the Medicaid lottery as an instrument for medical spending. To capture heterogeneity, we assume differences in $m$ can be captured by differences in state variables, $\theta^K$, that consist of measures of financial and health states from an initial survey (fielded essentially concurrently with the lottery). We construct a binary “financial constraint” variable that takes the value of 1 if the individual responded affirmatively to any of these questions: (i) whether or not the individual had to forgo medical treatment because of financial conditions (ii) whether or not the individual had to forgo prescription drugs because of financial conditions, and (iii) whether or not the individual was refused medical treatment due to inability to pay. Approximately 36% report having a financial constraint in this initial survey. We construct a binary health state variable that takes the value 1 if the individual was previously diagnosed with diabetes, asthma, high blood pressure, emphysema, congestive heart failure, or depression. Approximately 45% report having a major health diagnosis in this initial survey. The state variables $\theta^K$ consist of four dummy variables, each of which corresponds to one of the four values that the interaction of the financial state variable and the health state variable can take on.\(^{56}\) For each value of the state variables, we estimate the expected return to medical spending using the lottery as an instrument for medical spending.

Table A.2 reports the estimated IV results of the effect of medical spending on the health indicator. Consistent with the hypothesis that the value of insurance is higher to those who are more constrained, the IV estimates of the impact of medical spending on health are largest for those with financial constraints (columns III and IV). However, all of our estimates are very imprecise and none are statistically different from zero. Moreover, one should bear in mind that our measure of health is self-reported, and our measures of the state variables are quite coarse.

A.4 Construction of $-\frac{\partial x}{\partial q}$ when Medicaid recipients have positive out-of-pocket expenditures

When at least some Medicaid recipients have strictly positive out-of-pocket spending, the expression for the relaxation of the budget constraint at $q = 1$ becomes:

$$-\frac{\partial x}{\partial q} \bigg|_{q=1} = x(0, m(1; \theta)) - x(1, m(1; \theta)).$$

The second term, $x(1, m(1; \theta))$, is the distribution of out-of-pocket spending of the insured, which is given by the distribution of out-of-pocket spending by treatment compliers. The first term, $x(0, m(1; \theta))$ is the distribution that the uninsured would have had if they had had the medical spending of the insured. We follow the same procedure as in subsection 4.2, and approximate the

\(^{56}\)In principle, one could use more than four state variables; however, our estimates are already fairly imprecise with only four state variables and additional variables would further increase the already considerable noise in the estimates.
out-of-pocket spending schedule for the uninsured \((x(0,m))\) by assuming that it is linear in \(m\) and estimating the price as the ratio of mean out-of-pocket spending to mean total spending for the control compliers (i.e., \(\frac{\partial x}{\partial m|_{q=0}} = \frac{E[x(0,m(0;\theta))]}{E[m(0;\theta)]}\)). With the assumption of a constant price for the uninsured, we write:

\[
x(0,m(1;\theta)) = x(0;m(0;\theta)) + \left(\frac{\partial x}{\partial m|_{q=0}}\right)(m(1;\theta) - m(0;\theta)).
\]

By combining the two equations above, we obtain:

\[
\frac{\partial x}{\partial q|_{q=0}} = x(0,m(0;\theta)) - x(1,m(1;\theta)) + \left(\frac{\partial x}{\partial m|_{q=0}}\right)(m(1;\theta) - m(0;\theta)).
\]

This expression consists consists of the difference in the distributions of out-of-pocket expenditures of control compliers and treatment compliers plus the price faced by the uninsured times the difference in the distributions of medical spending of treatment compliers minus control compliers.

In the construction of differences in distributions, we assume quantile stability. In other words, we take the difference in distributions assuming an individual with a given \(\theta\) that puts him at quantile \(p\) in the control distribution would have been at quantile \(p\) in the treatment distribution if he had been in the treatment group.

The expression for the relaxation of the budget constraint at \(q = 0\) is derived analogously:

\[
\frac{\partial x}{\partial q|_{q=0}} = x(0,m(0;\theta)) - x(1,m(0;\theta)).
\]

The first term, \(x(0,m(0;\theta))\), is the distribution of out-of-pocket spending of the uninsured, which is given by the distribution of out-of-pocket spending by control compliers. The second term, \(x(1,m(0;\theta))\) is the distribution that the insured would have had if they had had the medical spending of the uninsured. We approximate the out-of-pocket spending schedule for the insured \((x(1,m))\) by assuming that it is linear in \(m\) and estimating the price as the ratio of mean out-of-pocket spending to mean total spending for the treatment compliers (i.e., \(\frac{\partial x}{\partial m|_{q=1}} = \frac{E[x(1,m(1;\theta))]}{E[m(1;\theta)]}\)).

With the assumption of a constant price for the insured, we write:

\[
x(1,m(0;\theta)) = x(1;m(1;\theta)) + \left(\frac{\partial x}{\partial m|_{q=1}}\right)(m(0;\theta) - m(1;\theta)).
\]

Hence, we have:

\[
\frac{\partial x}{\partial q|_{q=0}} = x(0,m(0;\theta)) - x(1,m(1;\theta)) + \left(\frac{\partial x}{\partial m|_{q=1}}\right)(m(1;\theta) - m(0;\theta)).
\]

A.5 Direct consumption measurement in the CEX

Data and sample The CEX consists of a series of short panels. Each “consumer unit” (CU) is interviewed every 3 months over 5 calendar quarters. In the initial interview, information is collected on demographic and family characteristics and on the consumer unit’s inventory of major
durable goods. Expenditure information is collected in the second through the fifth interviews using uniform questionnaires. Income and employment information is collected in the second and fifth interviews.

Our sample includes all CUs in 1996-2010 who have valid expenditure data in all 4 quarters (i.e., positive total expenditure and non-negative medical expenditure) and non-missing income data. To be broadly consistent with the Oregon sample, we further limit the analysis to adults aged 19-64 who are below 100% of the federal poverty line. We measure insurance status \( q \) at the start of the survey, regardless of whether or not the individual obtains insurance later in the year (results are quite similar if we use concurrent insurance status). Because the CEX only requests information on the health insurance status of the household head, we restrict the sample to single adults with no children in the household, so that we can identify the individuals who are uninsured and uninsured. We convert all dollar amounts to 2009-dollars, and impose an annual consumption floor (although in practice the baseline consumption floor of $1,000 never binds).

**Measuring the consumption covariance** We observe three variables: reported consumption, \( ˆc \), reported out-of-pocket medical spending, \( ˆx \), and an indicator for insurance status, \( i \in \{0, 1\} \). We wish to estimate

\[
\text{Cov} \left( \frac{c^{-σ}}{E[c^{-σ}]}, x | i = 0 \right),
\]

where \( c \) and \( x \) are actual consumption and out-of-pocket medical spending for those without formal insurance, \( i = 0 \). Table A.3 presents the results for our baseline specification and for alternative definitions of consumption, \( c \). For both the insured and uninsured, we compute \( c^{-σ} \) using \( σ = 3 \) and then compute the covariance between \( c^{-σ} \) and out-of-pocket medical spending, \( x \), normalized by the mean value of \( c^{-σ}, E[c^{-σ}] \).

As Table A.3 illustrates, these covariances for the uninsured are negative across all of our specifications. Although these results do not include any controls, this negative covariance persists even after controlling for a rich set of covariates including both time-invariant demographics and time-varying factors like income and wealth, as well as including consumer-unit fixed effects (results not shown). However, as can be seen in Table A.3, the covariance is more negative for the insured. We infer from this that the basic problem is that self-reported consumption and health spending may not equal the actual consumption and health spending. We outline a measurement-error model and a correction to it.

The core idea behind our particular measurement-error model is that individuals may misreport their out-of-pocket medical spending. If our model is correctly specified, the covariance between out-of-pocket medical spending and the marginal utility of consumption should be zero for the insured. Under the assumption that the measurement error for 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.

More formally, we observe non-medical consumption, \( ˆc \), and out-of-pocket medical spending \( ˆx \), and wish to infer the covariance between the marginal utility of consumption (normalized
by its average), $\frac{c - \sigma}{E[c - \sigma]}$, and true out-of-pocket medical spending, $x$. Here, our primary concern is mismeasurement of out-of-pocket spending, $x$. Therefore, we opt to allow for an arbitrary functional form on the shape of the distribution of this measurement error. In particular, we assume

$$\hat{x} = x + \epsilon$$

where $\epsilon$ is a measurement-error shock that is drawn from a distribution with unknown functional form that, importantly, may be correlated with the marginal utility of consumption.

We identify the covariance term even under this fairly general measurement-error structure by making three assumptions. First, we assume consumption is measured without error, $\hat{c} = c$, which implies that the marginal utility of consumption is also measured without error. Second, we assume that the joint distribution of the marginal utility of consumption and the measurement error are identically distributed for insured and uninsured. Third, we assume true out-of-pocket medical spending is zero for the insured, so that $\hat{x} = \epsilon$ for the insured. These assumptions would be satisfied if $\epsilon$ reflected consumption of uncovered healthcare for both the insured and uninsured (e.g., over-the-counter pain killers) and these are consumed in equal amounts by both groups.

Under these assumptions, the observed covariance between $\frac{\hat{c} - \sigma}{E[\hat{c} - \sigma]}$ and $\hat{x}$ for the insured provide an estimate of the bias induced by measurement error when estimating this covariance for the uninsured. The observed covariance between $\frac{\hat{c} - \sigma}{E[\hat{c} - \sigma]}$ and $\hat{x}$ is the sum of the true covariance and the measurement-error component:

$$Cov\left(\frac{\hat{c} - \sigma}{E[\hat{c} - \sigma]}, \hat{x} | i = 1\right) = Cov\left(c - \sigma, x | i = 0\right) + Cov\left(\frac{c - \sigma}{E[c - \sigma]}, \epsilon | i = 0\right).$$

Under our three assumptions, we can identify the measurement-error component from the insured:

$$Cov\left(\frac{c - \sigma}{E[c - \sigma]}, \epsilon | i = 0\right) = Cov\left(\frac{\hat{c} - \sigma}{E[\hat{c} - \sigma]}, \hat{x} | i = 1\right).$$

Hence, the true covariance term for the uninsured is given by the difference between the observed covariance for the uninsured and the insured:

$$Cov\left(\frac{c - \sigma}{E[c - \sigma]}, x | i = 0\right) = Cov\left(\frac{\hat{c} - \sigma}{E[\hat{c} - \sigma]}, \hat{x} | i = 0\right) - Cov\left(\frac{\hat{c} - \sigma}{E[\hat{c} - \sigma]}, \hat{x} | i = 1\right). \tag{37}$$

Of course, this is one particular model of measurement error, and the true measurement error could be of a different form. But, our approach has the advantage of allowing for an arbitrary shape on the unknown distribution of measurement error in out-of-pocket spending, $\epsilon$, and leads to an intuitive estimation strategy of using the estimated covariance term for the insured (which should be zero) to provide information about the true covariance term.

Table A.3 shows the results. Taking the difference between the covariance estimates for the insured and uninsured, as illustrated in equation (37), yields a covariance value of $\$251$ in the baseline specification. Dividing by 2 to form the linear approximation to the average covariance
value over \( q = 1 \) to \( q = 0 \), we have a pure-insurance value of $126 for the consumption first-order condition approach based on CEX data, as illustrated in Table 2. This estimate is largely similar if one chooses alternative measures of consumption, such food, education, reading, entertainment, and personal care (Column II), and all non-health consumption, excluding alcohol and tobacco (Column III).

Figure A1: Fitted and actual CDFs of out-of-pocket spending
Table A.1: Comparison with Prior Estimates from Finkelstein et al. (QJE, 2012)

<table>
<thead>
<tr>
<th></th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sample</td>
<td>QJE sample</td>
<td>Restricted sample</td>
<td>Restricted sample</td>
<td>Restricted sample</td>
</tr>
<tr>
<td>Data</td>
<td>Raw data</td>
<td>Raw data</td>
<td>Raw data</td>
<td>Adjusted data</td>
</tr>
<tr>
<td>Estimation Method</td>
<td>QJE paper</td>
<td>QJE paper</td>
<td>This paper</td>
<td>This paper</td>
</tr>
</tbody>
</table>

**First Stage: Lottery Impact on Insurance**

<table>
<thead>
<tr>
<th>Lottery Indicator</th>
<th>0.290</th>
<th>0.290</th>
<th>0.302</th>
<th>0.302</th>
</tr>
</thead>
<tbody>
<tr>
<td>(s.e.)</td>
<td>0.007</td>
<td>0.008</td>
<td>0.007</td>
<td>0.007</td>
</tr>
</tbody>
</table>

**IV: Impact of Medicaid on...**

<table>
<thead>
<tr>
<th>12-month medical spending</th>
<th>778</th>
<th>903</th>
<th>885</th>
<th>885</th>
</tr>
</thead>
<tbody>
<tr>
<td>(s.e.)</td>
<td>371</td>
<td>434</td>
<td>366</td>
<td>366</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>12-month out-of-pocket spending</th>
<th>-244</th>
<th>-364</th>
<th>-346</th>
<th>-489</th>
</tr>
</thead>
<tbody>
<tr>
<td>(s.e.)</td>
<td>86</td>
<td>104</td>
<td>78</td>
<td>38</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>self-reported health</th>
<th>0.133</th>
<th>0.103</th>
<th>0.142</th>
<th>0.142</th>
</tr>
</thead>
<tbody>
<tr>
<td>(s.e.)</td>
<td>0.026</td>
<td>0.032</td>
<td>0.028</td>
<td>0.028</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>did not screen positive for depression</th>
<th>0.078</th>
<th>0.060</th>
<th>0.059</th>
<th>0.059</th>
</tr>
</thead>
<tbody>
<tr>
<td>(s.e.)</td>
<td>0.025</td>
<td>0.030</td>
<td>0.026</td>
<td>0.026</td>
</tr>
</tbody>
</table>

| N                                  | 23,741 | 15,498 | 15,498 | 15,498 |

Notes: This table compares our baseline estimates of the impact of Medicaid with the baseline estimates of Finkelstein et al. (2012), which we refer to as "QJE." Self-reported health is a dummy variable that equals 1 if the individual reports being in good, very good, or excellent health. Column (I) replicates the QJE results. In column (II), we use the same regressions as in column (I) but now analyze a restriction of the QJE sample to respondents living in households that have at most 2 lottery tickets, and that have non-missing data on all the required variables (see Appendix A.1 for more details). In column III, we use the same sample as in column II but now the regression approach of this paper (again see Appendix A.1 for more details). In column IV, we use the estimation method and sample from this paper, applied to the "adjusted data" for out-of-pocket spending. "Adjusted data" refers to the out-of-pocket spending data after we (i) estimated it by fitting a lognormal distribution with a mass point at zero for the distribution of out-of-pocket spending, (ii) adjusting the out-of-pocket spending of the insured to be 0, and (iii) imposing a ceiling on out-of-pocket spending of (mean(income per capita) -consumption floor) for the uninsured; see text for more details. Column IV represents the data and approach used in this paper. All amounts are in dollars per Medicaid recipient per year.
Table A.2: Health Production Function Estimates

<table>
<thead>
<tr>
<th>Variable:</th>
<th>I</th>
<th>II</th>
<th>III</th>
<th>IV</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>No major health diagnosis, no financial constraint</td>
<td>Major health diagnosis, no financial constraint</td>
<td>No major health diagnosis, financial constraint</td>
<td>Major health diagnosis, financial constraint</td>
</tr>
<tr>
<td>First Stage: Lottery impact on Medical Spending</td>
<td>Lottery indicator</td>
<td>64</td>
<td>268</td>
<td>364</td>
</tr>
<tr>
<td></td>
<td>(s.e.)</td>
<td>(147)</td>
<td>(236)</td>
<td>(286)</td>
</tr>
<tr>
<td>Reduced Form: Lottery Impact on Health</td>
<td>Lottery indicator</td>
<td>0.032</td>
<td>0.006</td>
<td>0.040</td>
</tr>
<tr>
<td></td>
<td>(s.e.)</td>
<td>(0.011)</td>
<td>(0.018)</td>
<td>(0.025)</td>
</tr>
<tr>
<td>IV: Impact of Medical Spending on Health</td>
<td>$1000 in annual medical spending</td>
<td>-0.097</td>
<td>0.031</td>
<td>0.129</td>
</tr>
<tr>
<td></td>
<td>(s.e.)</td>
<td>(0.134)</td>
<td>(0.120)</td>
<td>(0.141)</td>
</tr>
<tr>
<td></td>
<td>Sample size (N)</td>
<td>6993</td>
<td>2886</td>
<td>1457</td>
</tr>
<tr>
<td></td>
<td>Mean out-of-pocket spending</td>
<td>296</td>
<td>362</td>
<td>279</td>
</tr>
</tbody>
</table>

Notes: Columns show results for four different subsamples, as defined in the text. Within each subsample results are analyzed controlling for number of lottery tickets. Medical spending and out-of-pocket spending are measured in dollars per year per Medicaid recipient. Health is a dummy variable that equals 1 if the individual reports being in good, very good, or excellent health.
<table>
<thead>
<tr>
<th>Definition of non-health consumption</th>
<th>Baseline</th>
<th>II</th>
<th>III</th>
</tr>
</thead>
<tbody>
<tr>
<td>All non-health Consumption</td>
<td>13,310</td>
<td>11,130</td>
<td>12,559</td>
</tr>
<tr>
<td>Food, education, reading, entertainment, personal care</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>All non-health excluding alcohol and tobacco</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Notes: This table presents baseline estimates for the consumption covariance term using the direct consumption measure (based on CEX data). The sample includes all single, childless consumption units in 1996-2010 who are complete income reporters and have valid expenditure data in all 4 quarters (i.e., strictly positive total expenditure and weakly positive out-of-pocket medical spending), and whose household head is between 19 and 65 years old in all 4 quarters, and with incomes not exceeding 100% of the Federal Poverty Line (N=1056). The numbers reported in the table are the covariances of marginal utility of non-health consumption (using a coefficient of relative risk aversion of 3) and out-of-pocket medical spending. To be consistent with the Oregon data, we impose a $1000 per capita annual consumption floor and convert all dollar amounts to 2009 dollars.