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ABSTRACT

Economists think of medical innovation as a valuable but risky good, producing health benefits but increasing financial risk. This perspective overlooks how innovation can lower physical risks borne by healthy patients facing the prospect of future disease. We present an alternative framework that accounts for all these aspects of value and links them to the value of health insurance. We show that any innovation worth buying reduces overall risk, thereby generating positive insurance value on its own. We conduct two empirical exercises to assess the significance of our insights. First, we calculate that conventional methods underestimate the value of historical health gains by 30-80%. Second, we examine a large set of medical technologies and calculate that insurance value on average adds 100% to the conventional valuation of those treatments. Moreover, we find that the physical risk-reduction value of these technologies is ten times greater than the financial risk they pose and the corresponding value of health insurance that insures this financial risk. Our analysis also suggests standard methods disproportionately undervalue treatments for the most severe illnesses, where physical risk to consumers is most costly.

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I. INTRODUCTION

Economists traditionally measure the benefit of a medical innovation as the improvement in health it produces in a person who is already sick (Drummond, Sculpher et al. 2005, Murphy and Topel 2006). Likewise, economists measure the benefit of health insurance by valuing the reduction in financial risk associated with lower out-of-pocket spending for medical care (Finkelstein and McKnight 2008, Abaluck and Gruber 2011, Engelhardt and Gruber 2011). Studying innovation and insurance in isolation, however, overlooks fundamental connections between them. As a result, the true economic benefit of medical technology has been inaccurately characterized and measured.

It is indeed true that a medical technology can improve the health of the sick, and that it can raise financial risk for the healthy. But it also does two other things that affect its valuation. First, a technology can reduce physical risk for healthy consumers who might get sick.[1] New treatments make illness less unpleasant and thus effectively raise utility in the bad state of the world, just like standard insurance contracts. Failure to account for this physical insurance value of technology understates its value, particularly in treating the most severe illnesses and the most risk-averse consumers. Second, medical technology does not merely create financial risk. Rather, it converts a previously uninsurable physical risk into a potentially insurable financial one (Philipson and Zanjani 2014). Medical technology thus enables health insurance to smooth a risk that it could not previously smooth, and its valuation should reflect that benefit.

We present a framework for valuing medical innovation that accounts for all of its benefits and costs, including its impacts on physical and financial risk. We show under general conditions that the reduction in physical risk outweighs the increase in financial risk, so that the net insurance value of innovation is positive.

To illustrate our key points, consider a healthy consumer facing the risk of developing Parkinson's disease[2] in the years before the discovery of treatments that reduced the disease's impacts on quality of life. Suppose we measure the quality of one year of life as some percentage of a year spent in perfect health. In the absence of a treatment, contracting Parkinson's might reduce quality of life from, say, 80% of perfect health to 40%.[3] Consider the introduction of a new medical treatment that costs roughly $5,000 per year and increases quality of life for Parkinson's patients from 40% to 70%. If the value of perfect health for one year is $50,000, this increase in quality of life is worth $15,000 annually but costs only $5,000 annually. The traditional approach in health economics compares these two numbers to arrive at the net value of the treatment, which in this case would be $10,000 annually.

Notice that this calculation neglects the way the medical treatment's introduction also compresses the *variance* in the quality of life between the Parkinson's and non-Parkinson's states. Prior to the availability of treatment, Parkinson's was a gamble that lowered quality of life by 40% of a perfectly

[1] Our paper focuses on medical innovations that reduce the cost of being sick. We take up the case of innovations that extend longevity in contemporaneous work.

[2] Parkinson's disease is a progressive disorder of the nervous system that degrades a patient's movements. It typically manifests as a hand tremor but can also cause slowing of movement and slurring of speech, and later dementia. Its most famous patient is the boxer Muhammad Ali. Parkinson's symptoms can now be treated with medications such as Levodopa or MAO-B inhibitors that raise the level of dopamine in the brain.

[3] To be clear, the numbers on the impact of Parkinson's on quality of life in this example are made up.

healthy year, or a loss of approximately $20,000 per year; the treatment transforms the disease into a new gamble that lowers quality of life by just 10% of a perfectly healthy year, or a loss of just $5,000 per year. This compression in quality of life outcomes generates value for consumers who dislike risk.

It is true that the reduction in the variance of health outcomes is mitigated by an increase in the variance of healthcare spending. Before the availability of treatment, the individual may have faced no financial risk from falling ill with Parkinson's; after its introduction, she faces the risk of a $5,000 per year expenditure. However, if the treatment is priced to generate consumer surplus, the ex post improvement in health outcomes will outweigh its financial cost. Thus, it should come as no surprise that this medical treatment lowers total risk in our example. Prior to the development of treatment, Parkinson's imposes a risk of losing $20,000 in reduced health. After development, the risk of disease is transformed into a $5,000 financial risk plus a $5,000 health risk. In sum, this medical treatment cut the total risk of Parkinson's in half. Furthermore, the nascent financial risk associated with purchasing treatment can be mitigated or even eliminated by health insurance.

More generally, the value of medical technology consists of its physical value and its financial value. As described in Table 1, each of these can be further decomposed into the value of: (1) changes in mean physical and financial outcomes; and (2) changes in the variance of physical and financial outcomes. We call the sum of the mean effects the "conventional value" of the technology, since this is what conventional economic analysis estimates.

Table 1: Elements in the value of medical technology.

	Mean	Variance
Physical value	Improvement in health outcomes	Lower health outcomes risk
Financial value	Increase in healthcare spending	Greater healthcare spending risk
Full value	**Conventional value**	**Insurance value**

Notes: Traditional cost-effectiveness analysis calculates the conventional value of medical technology. The spending risk component of insurance value is absent if the consumer has access to comprehensive healthcare insurance.

We call the sum of the variance effects the "insurance value" of technology. This component is not accounted for by conventional health economic analysis. Importantly, medical innovation coupled with well-functioning healthcare insurance eliminates the increase in healthcare spending risk and thus leads to unambiguous reductions in risk.

Our framework clarifies the relationship between the value of medical innovation and of health insurance. First, our model implies that medical technology itself acts as insurance. Even if a consumer has no health insurance, technology can reduce the physical risk she faces. In the Parkinson's example, she faced a health risk of $20,000 prior to the technology but just a $10,000 risk after it, even if no health insurance is available. Adding health insurance to the analysis would cause the risk to fall even lower, to just $5,000. Although health insurance magnifies the benefits of new technology, it is unable to smooth the initial $20,000 risk by itself because real-world financial markets rarely write contracts that make indemnity payments strictly on the basis of an illness occurring.[4] This insight has important implications for health policy. For example, providing consumers with access to better medical technology by encouraging medical innovation may reduce risk more efficiently than providing them with health insurance.

[4] One rare exception is Aflac Cancer Care, which pays a cash benefit upon diagnosis of cancer.

Second, our framework provides insights into the relationship between health insurance and medical technology. The existing literature has argued that these two products are complements by showing that the provision of health insurance can drive medical technology (Goddeeris 1984, Newhouse 1992).[5] Our framework highlights the possibility of reverse causality. Medical technology converts a physical risk (sickness) into a financial risk (payment for treatment) that can be mitigated by health insurance.[6] Thus technology, by making health insurance actually useful for smoothing health-related risk, generates demand for insurance (Weisbrod 1991).

Third, our framework allows economists to incorporate risk-reduction into existing estimates of the value from medical technology. This correction has the greatest empirical impact on treatments for severe diseases, where risks to consumers are greatest. This insight reconciles the conventional economic approach to valuation with the findings of population surveys suggesting that people prefer to allocate resources to treating severe diseases rather than milder ones, even holding fixed the cost-effectiveness of treatment across the two types of diseases (Nord, Richardson et al. 1995, Green and Gerard 2009, Linley and Hughes 2013). Conventional approaches are hard-pressed to account for this finding.

Our paper unites two large literatures. The first, which estimates the consumer surplus value of health and longevity, has found that advances in medical technology generate enormous value for consumers (Shepard and Zeckhauser 1984, Rosen 1988, Murphy and Topel 2006). Because these studies all operate within riskless environments, their estimates do not reflect any potential benefits accruing from risk reduction. A second, more recent literature has documented that health insurance delivers significant value to consumers (Engelhardt and Gruber 2011, Verguet, Laxminarayan et al. 2014). This is an important finding because it justifies the cost of public health insurance programs, even if they do not generate significant increases in overall health as several studies have found (Finkelstein and McKnight 2008, Baicker, Taubman et al. 2013). The framework used in these studies, however, is unable to compare the value of financial health insurance to the value of physical insurance provided by medical technology.

We undertake two empirical exercises to demonstrate the importance of our insights. First, we illustrate the extent to which conventional economic studies such as Murphy and Topel (2006) have underestimated the benefit of new medical technologies. The physical insurance value associated with aggregate quality-of-life improvements over the past 50 years adds 30-80% to the conventional value of quality-of-life improvements, depending on how those gains are distributed throughout the population.

[5] In general, health insurance is treated as an outward shift in the demand for medical technology (Acemoglu et al. 2006, Blume-Kohout and Sood 2008, Clemens 2013). However, Malani and Philipson (2013) observe that health insurance can reduce the supply of human subjects for the clinical trials required for medical innovation. Lakdawalla and Sood (2013) demonstrate that health insurance and medical innovation are complementary in the sense that health insurance reduces the static inefficiency from patents and thus reduces the cost of using patents to encourage innovation.

[6] Philipson and Zanjani (2014) make a related point in a paper written independently of and at the same time as this one. They add to this point the theoretical observation that investment in medical R&D can be interpreted as a premium payment that helps insure future health risk. By contrast, we add estimates to quantify empirically the distinct welfare contributions of medical technology and health insurance.

Second, we quantify the insurance value of a sample of medical technologies studied in the Tufts Cost-Effectiveness Analysis Registry (CEAR). For reasonable levels of risk aversion, we find that accounting for insurance value nearly the traditional estimated value of technology, on average. Moreover, the physical insurance value of technology is far greater than the financial insurance value of health insurance.

The remainder of this paper has the following outline. Section II provides a model that describes the different components of value of medical innovation. Section III presents the results of our empirical exercises. Section IV concludes.

II. FRAMEWORK FOR VALUING MEDICAL TREATMENTS

Consider an individual who faces a health risk. We are interested in calculating the value of a new medical technology that improves health in the sick state and is priced to generate non-negative consumer surplus even in the absence of health insurance.[7]

The individual derives utility from non-health consumption and from health according to $u(c,h)$. She is either sick with probability π, or well with probability $1-\pi$. Absent medical treatments, health is h^w when well and $h^s < h^w$ when sick. The individual is endowed with income y^w when well and $y^s \leq y^w$ when sick. Let u_j^i denote the marginal utility of good $j \in \{c,h\}$ in state $i \in \{s,w\}$.

We examine a medical treatment that promises an increase in health of Δh in the sick state at a price of p to be paid in the sick state. Our theoretical analysis will focus on valuing marginal doses of the technology, i.e., dh and dp, because that will yield the most intuitive expressions for the different components of value.[8] Our empirical framework, presented in the next section, allows technologies to have discrete benefits and costs. Our approach calculates a consumer's ex ante willingness to pay for a new technology. In the appendix we discuss how to value technology using certainty equivalents, a related approach.

A key assumption that we maintain throughout our paper is that consumers have positive demand for health insurance, i.e., that the marginal utility of consumption is higher in the sick state than in the poor state ($u_c^s > u_c^w$). This holds if one or both of the following are true: illness raises the marginal utility of consumption, by affecting the curvature of utility directly; or illness reduces consumption in the sick state by, for example, necessitating the purchase of medical care or reducing earnings, thereby increasing marginal utility as a result. The first condition is sometimes referred to as "positive state dependence." While there is no consensus among economists as to whether consumers exhibit positive state dependence, there is little doubt that the demand for health insurance is positive. Thus our theoretical analysis maintains the weaker assumption about insurance demand, without imposing a specific assumption around state dependence. We note that if this weaker assumption is violated, so that $u_c^s < u_c^w$, our results still obtain, but the sign of the value of insurance flips from positive to negative. In this case, both medical technology and health insurance exacerbate risk.

[7] In an earlier working paper version of this manuscript, we also show how to measure the value of technologies that reduce the probability of becoming sick.

[8] Note that allowing for endogenous investments in prevention does not affect our analysis. Consider, for example, a new therapeutic treatment for an infectious disease, which can be prevented by avoiding infected individuals. Assuming that prevention is chosen optimally, the envelope theorem implies that the choice of prevention level will have no impact on the value of a new treatment on the margin.

II.A. The conventional value of medical technology

The standard approach to valuing medical technology typically proceeds by quantifying how much patients are willing to pay for the technology in the sick state (Drummond, Sculpher et al. 2005). That value, V, is defined implicitly according to the following expression:

$$u(y^s - p - V, h^s + \Delta h) = u(y^s, h^s)$$

Taking the full derivative of this expression with respect to components of technology (Δh and p) and willingness to pay (V) shows the ex post marginal value of technology (dV) to sick patients is:

$$dV = \frac{u_h^s}{u_c^s} dh - dp$$

This expression is the difference between the technology's marginal benefit ($u_h^s dh$) and its marginal cost ($u_c^s dp$), normalized by the marginal utility of income (u_c^s).[9] The "conventional" value of health technology, dV_C, is simply this marginal value to sick patients multiplied by the probability of being sick:

$$dV_C = \pi \left(\frac{u_h^s}{u_c^s} dh - dp \right) \quad (1)$$

The conventional value of medical technology accounts for risk by scaling its ex post value by the probability of falling ill, π. This is akin to assuming consumers are risk neutral, which is unappealing. Indeed, risk is a primary focus of a large number of economic studies on health insurance (Finkelstein and McKnight 2008, Abaluck and Gruber 2011, Engelhardt and Gruber 2011).

The remainder of this section provides a more general approach that values medical technology ex ante, before the health state is realized, and explicitly accounts for risk preferences. In keeping with the terminology shown in Table 1, we will decompose total value into "conventional value" (dV_C) and "insurance value" (dV_I). We further break down insurance value into a "physical" (dV_{I_P}) and a "financial" (dV_{I_F}) component.[10]

We derive the total value under three different settings: "no health insurance" (dV^{NHI}), "with health insurance" (dV^{WHI}), and "complete indemnity insurance" (dV^{CII}).

II.B. The total value of technology in the absence of health insurance

We first assume consumers do not have access to health insurance in order to show that technology has risk-reduction value even in the absence of financial health insurance. The willingness to pay for a technology under "no health insurance," V^{NHI}, from the perspective of all consumers who face the relevant health risk, is implicitly defined by:

$$\pi u(y^s - p - V^{NHI}, h^s + dh) + (1 - \pi) u(y^w - V^{NHI}, h^w) = \pi u(y^s, h^s) + (1 - \pi) u(y^w, h^w)$$

[9] As mentioned earlier, our theoretical analysis models the marginal value of the introduction of a new technology. Mathematically, this means we evaluate the derivative at the point $u(y^s, h^s)$.

[10] Using the language of Ehrlich and Becker (1972), one could call dV_I "self-insurance value" when health insurance is absent because it measures the ability of technology alone to reduce risk, and call dV_{I_F} "market insurance value" because it reflects the ability of financial insurance to mitigate spending risk introduced by a new technology.

The marginal value in this case is given by the difference between the expected marginal benefit ($\pi u_h^s dh$) and the expected marginal cost ($\pi u_c^s dp$), normalized by the ex ante marginal utility of income ($\pi u_c^s + (1-\pi)u_c^w$):

$$dV^{NHI} = \frac{\pi(u_h^s dh - u_c^s dp)}{\pi u_c^s + (1-\pi)u_c^w}$$

Rearranging this expression shows that the value of technology with no health insurance, dV^{NHI}, can be expressed as the conventional value, dV_C, plus an additional component that reflects the insurance value of the technology, dV_I^{NHI}:

$$dV^{NHI} = \overbrace{\pi\left(\frac{u_h^s}{u_c^s}dh - dp\right)}^{\substack{Conventional \\ value,\ dV_C}} + \overbrace{\pi(1-\pi)\left(\frac{u_h^s}{u_c^s}dh - dp\right)\left(\frac{u_c^s - u_c^w}{\pi u_c^s + (1-\pi)u_c^w}\right)}^{Insurance\ value\ with\ no\ health\ insurance,\ dV_I^{NHI}} \quad (2)$$

Insurance value in the absence of insurance, dV_I^{NHI}, is always positive, provided that the technology is priced such that its conventional value is positive, and provided the individual has positive demand for financial insurance against the health risk (i.e., $u_c^s > u_c^w$). This important result bears repeating: even absent health insurance, any medical technology that is worth purchasing ex post reduces overall risk ex ante, because the reduction in physical risk more than offsets the increase in financial risk.

The insurance value of technology in the absence of health insurance can be written explicitly as the reduction in physical health risk minus the increase in financial risk:

$$dV_I^{NHI} = \overbrace{\pi(1-\pi)\left(\frac{u_c^s - u_c^w}{\pi u_c^s + (1-\pi)u_c^w}\right)\frac{u_h^s}{u_c^s}dh}^{Reduction\ in\ physical\ risk\ (dV_{I_P})} - \overbrace{\pi(1-\pi)\left(\frac{u_c^s - u_c^w}{\pi u_c^s + (1-\pi)u_c^w}\right)dp}^{Increase\ in\ financial\ risk\ (dV_{I_F})}$$

The reduction in health risk gets larger as the value of the health improvement, $\frac{u_h^s}{u_c^s}dh$, gets larger. The increase in spending risk gets larger as the technology's cost, dp, gets larger. Our empirical exercises will quantify the size of these two insurance components and compare them to the conventional value.

II.C. The total value of technology with health insurance

Health insurance mitigates the spending risk created by new technology and thus boosts the overall insurance value created when new technologies are introduced. Consider an actuarially fair, fee-for-service health insurance contract that pays the consumer $\bar{p}(p)$ when she falls sick.[11] When $\bar{p}(p) = p$, the individual has complete fee-for-service (FFS) health insurance; when $\bar{p}(p) < p$, the individual has incomplete FFS insurance due to, e.g., deductibles, co-payments, annual caps, or other patient cost-sharing features.

In this environment, the individual solves the problem:

$$\max_{\tau} \pi u\left(y^s - p + \frac{1-\pi}{\pi}\tau, h^s + \Delta h\right) + (1-\pi)u(y^w - \tau, h^w) \text{ subject to } \tau \leq \pi\bar{p}(p)$$

[11] Because the contract is actuarially fair, the insurance premium is equal to $\pi\bar{p}(p)$. This means a consumer in the sick state will receive a net transfer of $\bar{p}(p) - \pi\bar{p}(p) = (1-\pi)\bar{p}(p)$ when sick.

In practice, most consumers are not completely insured against health risks. Therefore, the transfer constraint will typically bind, and the consumer will choose $\tau^* = \pi\bar{p}(p)$.

Define V^{WHI} as the total value of technology "with health insurance". Using the expression for the optimal transfer τ^*, we can implicitly define this value as:

$$\begin{aligned}\pi u(y^s - p + (1-\pi)\bar{p}(p) - V^{WHI}, h^s + \Delta h) + (1-\pi)u(y^w - \pi\,\bar{p}(p) - V^{WHI}, h^w) \\ = \pi u(y^s, h^s) + (1-\pi)u(y^w, h^w)\end{aligned}$$

The corresponding marginal value of technology with health insurance (dV^{WHI}) is given by:

$$dV^{WHI} = \frac{\pi[u_h^s dh - u_c^s dp + (1-\pi)(u_c^s - u_c^w)\bar{p}'(p)dp]}{\pi u_c^s + (1-\pi)u_c^w} \tag{3}$$

We can relate dV^{WHI} to the earlier expression for conventional value, dV_C, and insurance value without health insurance, dV_I^{NHI}, according to:

$$dV^{WHI} = dV_C + dV_I^{NHI} + \overbrace{\pi(1-\pi)\left[\frac{u_c^s - u_c^w}{\pi u_c^s + (1-\pi)u_c^w}\right]\frac{d\bar{p}}{dp}dp}^{Value\ of\ health\ insurance,\ \ dV_I^{WHI}} \tag{4}$$

The value of technology with health insurance is equal to its conventional value, plus the insurance value that accrues without any health insurance available, plus a component that reflects the incremental value of health insurance made possible by technology.

If health insurance is complete, so that $\bar{p}(p) = p$, then it will perfectly offset and eliminate the financial risk introduced by the new technology. Mathematically, if $\frac{d\bar{p}}{dp} = 1$, then $dV_I^{WHI} = dV_{I_F}$. In this special case, the total value of technology is equal only to the conventional value plus the value of physical risk reduction:

$$dV^{WHI} = dV_C + dV_{I_P}$$

II.D. The total value of technology under complete indemnity health insurance

What happens if the consumer has access to perfect indemnity insurance, as opposed to health insurance covering only the cost of medical care? While rarely observed in practice, indemnity insurance is frequently assumed in economic models of health for analytical convenience (e.g., Murphy and Topel 2006). Because the consumer faces no constraints on the amount of money she can transfer across states, she will choose an amount $\tilde{\tau}$ that equalizes the marginal utility of wealth across states, even when she does not have access to medical technology:

$$u_c\left(y^s + \frac{1-\pi}{\pi}\tilde{\tau}, h^s\right) = u_c(y^w - \tilde{\tau}, h^w)$$

Full indemnity health insurance is fundamentally different from the healthcare insurance we considered earlier, because indemnity insurance operates even in the absence of medical technology. This means that the marginal value of a new technology is measured at the point $u\left(y^s + \frac{1-\pi}{\pi}\tilde{\tau}, h^s\right)$, not $u(y^s, h^s)$. We therefore denote the indemnity-insured marginal utility of good $j \in \{c, h\}$ in state $i \in \{s, w\}$ as $\tilde{u}_j^i$. Because $\tilde{u}_h^s = \tilde{u}_c^s$, it is straightforward to show that the value of a new medical technology under "indemnity insurance" is equal to

$$dV^{CII} = \pi\left(\frac{\tilde{u}_h^s}{\tilde{u}_c^s}dh - dp\right)$$

Notice that this expression is substantially similar to equation (1), the expression for the conventional value. In fact, if the marginal utilities for dV_C are calculated in the indemnity insured state, then $dV^{CII} = dV_C$. In that case, the conventional value of medical technology is equal to the value in a setting where consumers face no risk thanks to perfect indemnity insurance. In principle, some differences arise, because conventional approaches typically fail to calculate marginal utilities in the indemnity-insured state. Nonetheless, the structure of the conventional value calculation is identical to that of the indemnity insurance case. In other words, the conventional approach to valuing medical technology is correct and complete only in the highly unrealistic case of perfect indemnity health insurance.

II.E. Implications for valuing health gains

If individuals are risk averse and have positive demand for health insurance—which empirical evidence suggests is true—then our model shows that the conventional valuation of medical technology underestimates the true value. This has important implications for cost-effectiveness analysis, which is widely employed by healthcare systems across the world to determine which medical treatments qualify for insurance coverage. Moreover, economic studies such as Murphy and Topel (2006) abstract away from the insurance value of technology and thus exclude an important source of value associated with health improvements.[12] We return to this point in our empirical section.

Our results also have important implications for the relative values of different types of medical technologies. This can be seen by examining the effect of health status in the sick state, h^s, on our analytical expressions for the value of a marginal technology. This is of particular interest because low values of h^s reflect diseases with high "unmet need", e.g., Parkinson's disease, hepatitis C, or amyotrophic lateral sclerosis (ALS). There is much contemporary debate concerning how much insurers should pay to treat these diseases. Suppose, as is empirically realistic, that the marginal ex post willingness to pay for health improvement is falling in the baseline level of health, i.e., people who are sicker have higher willingness to pay for a given health improvement, and vice-versa.[13] This assumption is supported by survey evidence suggesting that people value a given level of health investment more highly when provided to sicker patients (Nord, Richardson et al. 1995, Green and Gerard 2009, Linley and Hughes 2013). If this assumption obtains, two results follow. First, the total value of a medical technology is higher for diseases with a higher degree of unmet need (i.e., diseases associated with low values of h^s). Second, the difference between the conventional value and the total value grows as the degree of unmet need rises. This suggests that errors in the use of the standard approach are most likely for severe diseases with a poor current standard of care.

[12] Although consumers in Murphy and Topel (2006) have uncertain lifespans, their quality of life at any given age is known with certainty and they have access to perfect credit markets. Thus health insurance has no value in their model.

[13] It is straightforward to show that this is equivalent to assuming $u_c^s u_{hh}^s - u_h^s u_{ch}^s < 0$. This condition necessarily holds for certain classes of utility functions, including the Cobb-Douglas specification we employ in our empirical exercises.

III. EMPIRICAL ESTIMATES OF THE VALUE OF MEDICAL INNOVATION

We now present results from empirical exercises designed to quantify the insurance value of medical innovation at an aggregate level, and at the level of individual medical technologies. We first describe our estimation framework and explain how we parameterize our empirical model. We then conduct two different calibration exercises. The first employs data from a nationally representative set of individuals to estimate the aggregate insurance value that follows from increases in the quality of life. The second exercise employs data from the Cost-Effectiveness Analysis Registry to generate technology-level estimates of value for a large set of real-world therapeutic innovations.

III.A. Estimation framework

Following the existing literature on how health affects preferences for investment risk (Picone, Uribe et al. 1998, Edwards 2008), we assume that consumers have Cobb-Douglas period utility over consumption and health:

$$u(c,h) = \frac{(c^{\gamma}h^{1-\gamma})^{1-\sigma} - 1}{1-\sigma} \text{ if } \sigma \neq 1$$
$$u(c,h) = \ln(c^{\gamma}h^{1-\gamma}) \text{ if } \sigma = 1$$

where $\gamma \in (0,1)$ affects the marginal rate of substitution between consumption and health and $\sigma \geq 0$ affects the curvature of the utility function. The parameter γ primarily drives the conventional value of technology while the parameter σ drives risk aversion and thus the insurance value of technology. This utility specification is convenient because it separates risk-aversion from the conventional value placed on improvements in health.[14] This allows us to hold the conventional value of technology constant when estimating the effect of risk aversion on insurance values.

We are only aware of one study that estimates the parameter γ. Edwards (2008) examines the effect of health risk on investment decisions and concludes that a range of 0.155 to 0.443 for γ best fits the data. We therefore set $\gamma = 0.3$ in our analysis. Employing alternative values of γ affects the levels of our estimates, but does not substantively change our conclusions concerning the importance of insurance value relative to conventional value.

We calibrate the parameter σ using estimates from studies of risk aversion. The Arrow-Pratt measure of relative risk aversion over consumption in our Cobb-Douglas utility specification is equal to $R^c = 1 - \gamma(1-\sigma) > 0$ (Dardanoni 1988). The proper value of risk aversion among real-world populations remains controversial. Chetty (2006) estimates a risk aversion range of 0.15 to 1.78, but many studies have estimated much larger values.[15] We adopt $\sigma = 3$ as our preferred estimate, which corresponds to a relative risk-aversion value of $R^c = 1.6$, but we also report results across a broad range of risk assumptions.

[14] We also considered a multiplicative utility model $u(c,h) = hu(c)$. The advantage of multiplicative utility is that it separates the effect of risk aversion from the effect of state dependence. One disadvantage, however, is that it does not allow one to separate risk aversion from what we call the conventional value, i.e., changes in risk preferences affect ex post valuations, which is unappealing.

[15] A less than comprehensive list includes Barsky et al. (1997), Cohen and Einav (2005), Kocherlakota (1996), and Mehra and Prescott (1985).

Note that the parameter σ also determines the effect of changes in health on the marginal utility of consumption. If $\sigma < 1$ ($\sigma > 1$), the marginal utility of consumption declines (increases) in the sick state, i.e., there is negative (positive) state dependence. If $\sigma = 1$ then the marginal utility of consumption is independent of health, i.e., state-independent utility. All else equal, the value of transferring resources from the well state to the sick state is increasing in σ. Because there is less agreement regarding the sign, let alone the magnitude, of the state dependence of the utility function as opposed to risk aversion, we select σ based on estimates of risk aversion rather than state dependence.[16] However, we point out that our preferred choice of $\sigma = 3$ also implies positive state dependence. We run calibrations with different values of σ to show how robust our estimates of the insurance value of technology are to risk aversion, but these also show the effects of state dependence.

Unless otherwise noted, we assume throughout that income in both the sick and well states, y^S and y^W, is equal to \$120,000, which is approximately the value of full income for a typical individual (Murphy and Topel 2006). Full income here embeds all sources of non-health consumption, including leisure. Assuming $y^S = y^W$ provides a conservative estimate of insurance value, because it minimizes the benefits of transferring wealth from the healthy state to the sick state by failing to incorporate the documented empirical finding that poor health tends to decrease income (Smith 1999). Employing an alternative, lower value for y^S would increase our estimates of both the conventional and insurance values of technology, as shown in the appendix.

Our calibration exercises require us to measure health in some manner. We accomplish this by employing quality of life measures from our data sets, described below. Because health has no natural units, all measures are normalized without loss of generality so that they range from 0 to 1. These endpoints can be thought of as representing "death" and "perfect health," respectively. The subjective nature of the data and the multidimensional nature of health mean these measures are necessarily imperfect. Nevertheless, we build on established literatures of health measurement in order to lend our measurement strategy a firmer foundation.

We report all estimates of insurance value from an ex ante perspective. Thus, they should be regarded as the values accruing to an individual who is facing a risk of illness rather than to an individual who is already ill. Appendix A provides details on how we implement our calculations, and also generalizes our main model to accommodate an arbitrary number of sick states.

Our calibration exercises will estimate the conventional and insurance values of technology. We also decompose insurance value into its two subcomponents: physical insurance value and financial spending risk (see Table 1). Absent health insurance, the total value of technology is equal to the sum of conventional value, physical insurance value, and the offsetting financial spending risk. If complete fee-for-service health insurance is available, financial spending risk is equal to 0 and the total value of technology is then equal to the conventional value plus physical insurance value.

Before we turn to our empirical calculations, we illustrate how these various components of value change as a function of a technology's price, given our parameter assumptions. Figure 1 displays the results for the case where $h^S = 0.8$ and $\Delta h = 0.2$. Since perfect health corresponds to $h = 1$, this

[16] Finkelstein et al. (2013), Sloan et al (1988), and Viscusi and Evans (1990) find evidence of negative state dependence. Edwards (2008) and Lillard and Weiss (1988) find evidence of positive state dependence. Evans and Viscusi (1991) find no evidence of state dependence.

hypothetical technology represents a perfect cure. The total value of this technology to a consumer is equal to about $7,000 when the price is zero. In other words, a consumer facing the risk of falling ill is willing to pay $7,000 for access to a free medical treatment that cures this illness. Figure 1 shows that this $7,000 can be decomposed into about $5,000 of conventional value and $2,000 of physical insurance value. At a price of zero, the financial spending risk of the technology is nonexistent.

Figure 1 demonstrates that the conventional value, which ignores risk entirely, decreases linearly with price. The financial spending risk increases nonlinearly with price. Physical insurance value, by contrast, is unaffected by changes in price.

The total value of the technology depends on whether or not the consumer is insured. As shown in Figure 1, price increases reduce total value more for the uninsured than the insured. The difference between the "total (insured")" and "total (uninsured)" lines in Figure 1 is equal to the financial spending risk and represents the value of health insurance. This difference is small when the price is low, but becomes large when the price is high.

III.B. Aggregate value of gains to quality of life

There is substantial evidence that the average quality of life has improved dramatically over the past fifty years. The proportion of elderly who are disabled has decreased, and the proportion who are active has increased (Cutler 2005). Previous work has estimated that the increase in quality of life is actually more valuable than the accompanying increase in life expectancy (Murphy and Topel 2006). Our first calibration exercise aims to understand how this value changes when one accounts for the insurance value of medical innovation.

We accomplish this by estimating the lifetime benefits of an increase in quality of life, Δh, comparable to that considered in Murphy and Topel (2006), using data from a nationally representative sample of individuals from the Medical Expenditure Panel Survey (MEPS). We assume the price of technology is zero, which means our simulated increase in quality of life will generate physical insurance value without any offsetting financial risk. We show in the appendix that relaxing this assumption does not alter our main conclusions.

The theoretical model presented in the first half of this paper allowed for only one possible sick state. Here we employ a generalized version that allows for an arbitrary number of sick states. The health status and probability of a particular state i are given by h^{s_i} and π_i, respectively. A medical technology can improve the health of any state i by an amount Δh_i for price p_i. See the appendix for details.

Let $f(h^s)$ represent the distribution of health risks. We measure h^s as "quality of life," employing a widely used and well-validated tool for measuring quality of life known as the EQ-5D (or EQ-5D-3L). The EQ-5D measures quality of life on a scale from zero to one, using answers from five survey questions regarding the extent of the respondent's problems in mobility, self-care, daily activities, pain, and anxiety/depression. All these questions are asked of respondents in the 2000-2003 MEPS, which serves as our host database.

We use the EQ-5D measure to estimate baseline health state quantiles by age group and gender. Our results are reported in Table 2. The table shows that the 10th percentile of health status for 18-34-year-old males is equal to an EQ-5D score of 0.726. For each quantile, health status declines with age, as expected. Conditional on age, males are estimated to have a higher quality of life than females. In every group, the 90th percentile enjoys perfect health. In our analysis, we assume that each health status

displayed in Table 2 represents a health status in an untreated sick state, h^{si}. For each gender and age group, there are nine possible states, each occurring with probability $\pi_i = 1/9$.

Next, we estimate how much a consumer facing the health risk distribution described in Table 2 would be willing to pay, ex ante, for a hypothetical average increase in her quality of life. How these hypothetical health gains are distributed across states will matter, because risk-averse individuals value gains in poor health states significantly more than gains in good health states. We therefore consider two different scenarios. The first scenario increases the quality of life in each state by 0.05, subject to the constraint that the total not exceed 1. The second scenario involves the same total increase in health, but concentrates all of the gain in the two poorest health states. In both cases, the average health increase is in line with the hypothetical increase considered by Murphy and Topel (2006).[17]

Our results for the first scenario are displayed in Table 3. They show that the total value of the health increase is equal to $6,634 for males between the ages of 18 and 34. This total can be broken down into $5,290 of conventional value and $1,344 of insurance value. Because we assume that price is equal to zero, this insurance value consists solely of physical insurance value without any remaining financial risk. Both the conventional and insurance values are generally increasing with age because the elderly are less healthy and thus have more to gain from health improvements. Young individuals, by contrast, already have a high probability of enjoying perfect health, which cannot be improved. The conventional value is responsible for the bulk of the health gain when individuals are young, but the fraction of the gain due to insurance increases steadily with age. This is due to the large dispersion in health states for the elderly, as shown in Table 2. Because the elderly face the most health risk, they enjoy the highest insurance value from an increase in the quality of life.[18]

Our results for the second scenario are displayed in Table 4. As expected, the total value of the health gains is larger than those presented in Table 3 because these gains are concentrated in the poorest health states. For the oldest age groups, the insurance value of the health gains significantly exceeds the conventional value.

We calculate the aggregate per capita life-time value of these health gains for an 18-year-old by aggregating over age groups in both scenarios. We discount our calculations by the probability of survival and by a real rate of discount equal to three percent.[19] The results, displayed in Table 5, show that the hypothetical health increase we consider generates about $209,000-$221,000 and $267,000-

[17] Murphy and Topel (2006) assume that advances in quality of life are related to the declines in mortality from 1970-2000. Life expectancy for 18-year-olds increased by about 5 percent during that period. Our hypothetical quality of life increase, when averaged equally across gender, age, and health states, increases the average index by about 4 percent.

[18] One exception is that the insurance value of technology is actually *lower* for 65-79-year-old males compared to some younger ages. As shown in Table 2, the bulk of the health reduction occurring between the 50-64 and the 65-79 age groups happens in the 60th percentile, which represents individuals who are healthier than average. This compresses the dispersion in health between the healthy and sick, thus reducing the benefits of risk reduction.

[19] Survival probabilities are obtained from www.mortality.org. Discount rates are calculated for the midpoint of the age group. For example, the expected conventional value for an 18-year-old male for the period covering ages 18-34 is equal to $\$5{,}290 \times 17 \times 0.99886/(1+0.03)^{17/2}$, where the first term comes from Table 3, $17 = 34 - 18 + 1$, the third term is the probability of surviving from age 18 to age 35, and the last term is the discount rate.

$285,000 in conventional value for an 18-year-old male and female, respectively. This is in line with the range estimated by Murphy and Topel (2006) for that age.

We also compute that the insurance value adds 27-81% to the conventional value, as shown in Table 5. This suggests that the value of advances in the quality of life may be significantly higher than has previously been recognized, and that the magnitude depends greatly on how those gains were distributed across the population.[20] The value is greatest if it accrues to the sickest individuals (those with a high degree of "unmet need"), and lowest if it accrues to those who were already relatively healthy. This reflects our earlier theoretical result that the difference between the conventional value and the total value of health gains grows with the degree of unmet need. To date, relatively little attention has been paid to the *distribution* of historical health gains, and how it influences the total social value of those gains.

III.C. Value of individual medical innovations

In our second calibration exercise, we calculate the conventional value and insurance value for real-world therapeutic technologies. In order to compute the components of value for a particular technology, we need data on four parameters: the annual price of the technology (p), the baseline health level prior to treatment (h^s), the perfectly well health level (h^w), and the annualized health improvement produced by the technology (Δh). In our exercise, we set $h^w = 1$. We obtain the remaining data from the Cost-Effectiveness Analysis Registry (CEAR). CEAR is a collection of several thousand cost-effectiveness studies published between 1976 and 2012.[21] A study is included in the database if it (1) contains original research; (2) measures health benefits in uniform units called Quality-Adjusted Life Years (QALYs); and (3) is published in English.

A QALY ranges from zero to one. It incorporates changes in both morbidity and mortality, and converts them into an "equivalent" number of "years of good health." For example, if individuals are indifferent between living nine months in perfect health and living twelve months on dialysis, then one year of life on dialysis is considered equal to $9/12 = 0.75$ "quality-adjusted" years. QALYs thus provide a convenient, standardized metric for comparing health benefits across different treatments.[22]

Our theoretical model pertains to changes in current period health, or morbidity. We therefore limit our analysis to technologies most likely to affect only morbidity, as described below. Nevertheless, one shortcoming of the CEAR data is that its measure of health improvement does not distinguish between longevity improvements and morbidity improvements. Attributing the improvement entirely to a decrease in morbidity will thus cause upward bias in our estimation. However, we are primarily interested here in estimating the insurance value of technology *relative* to the conventional value. Our results are substantively unchanged if we conservatively assume, for example, that only one-half of the

[20] Like most insurance studies, we implicitly assume that health shocks are uncorrelated over time. Relaxing this assumption would increase the value of insurance because correlated shocks imply even greater physical risk (Kowalski 2015).

[21] See research.tufts-nemc.org/cear4/AboutUs/WhatistheCEARegistry.aspx for more information.

[22] Employing QALY's imposes restrictions on the risk structure of the utility function when operating in an environment that allows for changes in both longevity and morbidity (Bleichrodt and Quiggin 1999). However, we are only estimating the value of changes in morbidity, which allows for a more general specification of the utility function (Hammitt 2013).

health improvement is due to a decrease in morbidity. Moreover, our results throughout can still be interpreted as demonstrating how insurance value evolves as current period health varies, since the precise identity of the medical technologies in the CEAR database is not central to our key conclusions.

The annualized price of treatment (p), health improvements (Δh), and the health baseline (h^s) are easily recovered from cost-effectiveness data. For example, a typical study computes costs and benefits over a horizon of T periods as:

$$Cost = Price = \sum_{t=0}^{T-1} p_t \left(1 - r_p\right)^t$$

$$Benefit = \sum_{t=0}^{T-1} \Delta h_t (1 - r_h)^t$$

The total cost of an intervention depends on the annual incremental cost, p_t, and is discounted at the rate r_p over a time horizon of T years. The total benefit is measured in annual incremental QALYs, Δh_t, and is discounted at the rate r_h.[23] The cost-effectiveness ratio is equal to $Cost/Benefit$.

The majority of cost-effectiveness studies do not specify an entire time path for $\{p_t, \Delta h_t\}$. Therefore, we make the simplifying assumption of a constant flow every period, characterized by $\{p, \Delta h\}$. These constant flow values are easily derived from the equations above, given information on total cost, total benefit, discount rates, and time horizon, by imposing the constraints that $p_t = p$ and $\Delta h_t = \Delta h$. Given the assumption of constant utility flow, it is without loss of generality that we consider the *annualized* cost and health benefit of medical technologies. Thus, Δh reflects the annual improvement in health enjoyed by a patient, and p reflects the annual price paid for the associated technology.

CEAR reports estimates of cost-effectiveness ratios ($Cost/Benefit$) for a wide variety of diseases and treatments. We exclude studies that do not report estimates of $Cost$ and $Benefit$ separately and that do not report time horizon or discount rates. CEAR classifies each study into different intervention types. We confine our attention to treatments, rather than preventive technologies (e.g., vaccines), and thus include any CEAR study classified as "pharmaceutical", "surgical", "medical device", or "medical procedure."[24] CEAR provides information on the total cost, total benefit, discount rates, and time horizon for each study.[25] As mentioned above, these data elements are sufficient to estimate the annual flow terms, $\{p, \Delta h\}$.

CEAR also reports the "health state utility weights" for each of the health states considered by a particular cost-effectiveness study. These cardinal measures range from zero to one and are used to proxy for h^s, the quality of life in the pre-treatment (sick) state. For example, suppose there are two health states, A and B, representing patients at different levels of illness severity. These two states

[23] The discount rates r_p and r_h are usually equal to each other. Only 8% of the studies in CEAR discount costs and benefits using different rates.

[24] The excluded categories are "care delivery", "diagnostic", "health education or behavior", "immunization", "none/na", "other", and "screening".

[25] Some studies report a time horizon of "lifetime" rather than a specific number of years. In those cases we assume a horizon of 85 years.

correspond to the utility weights w_a and w_b. If, prior to treatment, half of the patients are in health state A and the other half are in B, then $h^s = (w_a + w_b)/2$. Since CEAR does not report what fraction of the patients is in each health state for either the pre- or post-treatment groups, we assume that pre-treatment patients are uniformly distributed across health states.

CEAR assigns each treatment to one of seventy different disease categories. We match each category to nationally representative estimates of annual disease incidence obtained from the Medical Expenditure Panel Survey. See the data appendix for details.

Our final sample of therapeutic medical technologies consists of 1,797 observations. Summary statistics are provided in Table 6. Figure 2 displays the distribution of Δh, in units of annual QALYS gained, in our sample of therapeutic innovations. The majority of treatments produce small, annualized improvements in health ($\Delta h < 0.05$), but a few treatments produce large improvements, which skews the sample to the right. For example, drug treatments for chronic hepatitis B infections increase the annual quality of life by $\Delta h = 0.31$ QALYs.

Figure 3 displays the distribution of treatment prices in this sample. The sample is again skewed to the right, with the vast majority of treatments costing less than $5,000. Three very expensive treatments top the list with prices of approximately $150,000 per year: left ventricular assist devices for heart-failure patients and two different inhibitors for treatment of hemophilia. Although expensive, each of these three treatments generates large annual health improvements ($\Delta h \approx 0.15$). Not all expensive treatments are valuable, however: interferon beta-1b, a treatment for multiple sclerosis that helps prevent patients from becoming wheelchair-dependent, costs $22,000 per year but generates little annual health improvement ($\Delta h = 0.009$) (Forbes, Lees et al. 1999).

We now turn to the calculations from our model. Figure 4 shows that the distribution of the conventional value of medical technology in our CEAR sample is concentrated near zero and skewed to the right. This indicates that outliers will have a significant influence on mean values, and that analysis by quantiles may provide useful information. Figure 4 also shows that there are several technologies that generate negative conventional value, i.e., the ex post costs of these technologies exceed the ex post benefits.

Table 7 reports the mean, the median, and the 90th percentile of our calculations for values of σ ranging from 0.5 to 8, which corresponds to a relative risk aversion range of 0.85 to 3.1. The mean conventional value is equal to $769 and is unaffected by a consumer's risk preferences. The average physical insurance value and financial spending risk for our preferred specification of risk, $\sigma = 3$, are $883 and $45, respectively. The difference between these two values, $838, represents the net insurance value when consumers lack access to health insurance. The magnitudes of the calculated insurance values are increasing in σ because that parameter is linked to risk aversion, which boosts insurance value. The means of our estimates are substantially larger than the medians due to the skewness of the distribution (see Figure 4).

When σ is less than 1, consumers exhibit negative state dependence and will not demand insurance in the sick state unless the price of treatment is sufficiently large. This is reflected in negative spending risk values in the first row of Table 7. When σ is greater than 1, spending risk is positive for any treatment with a positive price.

Table 8 normalizes the insurance values displayed in Table 7 by the corresponding conventional value. When evaluated at the mean for $\sigma = 3$, it shows that each dollar of conventional value generates $1.15

of physical insurance value and $0.06 of offsetting financial spending risk. In other words, properly accounting for the total insurance benefits of therapeutic innovation increases its value by 109%. If the consumer has access to perfect fee-for-service health insurance, which eliminates financial spending risk, then the value would increase by 115%.

The average financial spending risk is small because the prices of most of the treatments in our sample are low relative to annual income. The magnitude increases substantially when the price of treatment is a significant fraction of an individual's wealth, as Figure 5 vividly demonstrates. This agrees with the notion that insurance is more valuable for expensive items than for cheap items.

Financial risk is highest for expensive technologies. Likewise, physical risk is highest for diseases that result in very poor health states. We would therefore expect that physical insurance value is largest for medical technologies that treat patients with low health status. This intuition is confirmed in Figure 6. The physical insurance value of technologies that treat severe diseases is vastly larger than those that treat mild conditions.[26]

Our calculations can be employed to compare consumers' willingness to pay for the physical insurance value of technology to their willingness to pay for health insurance that eliminates financial spending risk. According to Table 8, medical technology creates almost 20 times as much physical insurance value as health insurance ($1.15 vs. $0.06 of value) when evaluated at the mean.

Treatments for diseases with high "unmet need", defined in our framework as diseases with low values of h^S, are of particular interest, because there is much controversy surrounding their reimbursement. Survey evidence indicates that people believe that, all else equal, it is more beneficial to treat patients whose baseline level of health is lower. Moreover, even health technology assessment authorities known for their strictness tend to agree with this view, and often make coverage exceptions for expensive drugs that treat conditions where the need for new treatments is extreme, e.g., orphan diseases with few options and terminal diseases like cancer (Lancet, 2010).

An extreme example is a cost-effectiveness study of Infliximab, a treatment for Crohn's disease (Bodger, Kikuchi et al. 2009). The treatment group in this study consisted of patients with severe Crohn's disease, an extraordinarily painful inflammatory bowel disease that can affect several organ systems at the same time. These patients are assigned an h^S value of 0.103, the lowest in our data. Given a cost of $600 per year, a traditional framework that ignores insurance value would estimate that Infliximab generates $1,700 in conventional value for a consumer at risk for this illness. Accounting for risk aversion adds $15,200 in insurance value to the total value of Infliximab, an enormous increase.

Figure 7 illustrates how the total value of medical technology, including the insurance value, varies by patient health status for the entire sample of treatments we consider. Treating patients with low health status is very valuable. Figure 8 reveals that most of that value is generated by insurance, the component ignored by the traditional valuation of medical technology. Figure 9 illustrates this same point by showing that the conventional value significantly undervalues treatments for very ill patients. This suggests that – in line with public opinion – the standard approach to valuation is most inappropriate in cases where patients are extremely sick.

[26] Figure 6 does not account for the magnitude of the health improvement, Δh, which is a potential confounder. However, the correlation between the severity of disease and Δh is quite weak. Controlling for Δh in a formal regression framework does not alter this result.

Finally, we note that the calculations presented so far are conservative because we have assumed that the parameters governing income in the sick and well states are both equal to $120,000. If income in the sick state is lower, as is often the case for debilitating diseases like multiple sclerosis or Parkinson's disease, then the insurance value of treatment will increase because the value of being able to transfer resources from the well state to the sick state increases. We show in the appendix that if income in the sick state, y^S, is equal to $60,000 instead of $120,000, then physical insurance value is about three times larger than the conventional value, and the value of health insurance is about two-thirds as large as the conventional value.

IV. CONCLUSION

When real-world health insurance markets are imperfect, risk-averse consumers derive value from medical technologies that limit the consequences of bad events and thereby expand the reach of financial health insurance.

These theoretical observations are empirically meaningful. New medical technologies provide substantial insurance value above and beyond standard consumer surplus. Under plausible assumptions, the insurance value is roughly equal to the conventional value. Accounting for risk thus doubles the value of medical technology over and above conventional calculations. Notably, the physical insurance value of therapeutic technology is often a much larger contributor to insurance value than the financial insurance value created by healthcare insurance. The latter point suggests that medical technology on its own may do more to reduce risk than health insurance.

Our argument also suggests that the academic literature, which tends to focus exclusively on the standard consumer surplus value of medical technology, may have failed to capture a major part of its value. For example, Murphy and Topel (2006) value health increases over the past century at over $1 million per person. Our results suggest that accounting for uncertainty could significantly increase their estimates, by anywhere from 30-80%.

The ability of medical innovation to function as an insurance device influences not just the level of value, but also the relative value of alternative medical technologies. The conventional framework understates the value of technologies that treat the most severe illnesses, compared to technologies that treat mild ailments. This helps explain why health technology access decisions driven by cost-effectiveness considerations alone often seem at odds with public opinion. For example, survey evidence suggests that representative respondents evaluating equally "cost-effective" technologies strictly prefer paying for the one that treats the most severe illness (Nord, Richardson et al. 1995).

From a normative point of view, our analysis also implies that the rate of innovation functions in a manner similar to policies or market forces that complete or improve the efficiency of insurance markets. Increases in the pace of medical innovation reduce overall physical risks to health, and thus function in a manner similar to expansions in health insurance. As a result, policymakers concerned about improving the management of health risks should view the pace of medical innovation as an important lever to influence and maintain. U.S. policymakers have focused their efforts on improving health insurance access and design. While these are worthy goals, medical innovation policy may have an even greater impact on reducing risks from health.

More practically, our analysis informs the contemporary debate over how new medical technologies should be reimbursed. The United Kingdom provides an instructive example, as the UK health

authorities hew closely to the use of ex post consumer surplus as a measure of value for a new technology, and thus a guide to how generously it should be reimbursed. Perhaps as a result, the UK performs poorly in the reimbursement of drugs to treat cancer, which has motivated legislators there to provide exceptional reimbursement for such products, above and beyond what the UK health authorities dictate (Lancet, 2010). Controversy has erupted over the appropriateness of this approach, and the legislation has drawn a great deal of criticism (Lancet, 2010). Yet, our analysis illuminates how the severe nature of cancer might contribute to the major misalignment between the standard economic approach to valuing medical technology and the preferences of legislators and voters. The policy lesson is that more attention needs to be paid by third-party payers and other health policymakers to covering treatments for severe diseases in order to align payment policies with the values of consumers. Moreover, the standard economic approach to valuing health technology should itself work towards alignment with the preferences of healthy consumers and sick patients.

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APPENDIX

A. Accommodating multiple sick states

The model presented in the main text allowed for two health states, one sick and one well. Here we generalize the model to allow for an arbitrary number of sick states. Let the probability of each sick state be π_i, where $i = 1 \dots N$. Define the probability of the well state as $1 - \pi = 1 - \sum_{i=1}^{N} \pi_i$. Suppose that, for each sick state, there is a medical technology available that increases health by an amount Δh_i for a price p_i. The conventional value is equal to

$$V_C = \sum_{j=1}^{N} V_{C_i}$$

where each V_{C_i} is defined implicitly as

$$u\left(y^{s_i} - p_i - V_{C_i}/\pi_i, h^{s_i} + \Delta h_i\right) = u(y^{s_i}, h^{s_i})$$

The full ex ante willingness to pay for a technology under "no health insurance" is defined implicitly as

$$\sum_{i=1}^{N} [\pi_i u(y^{s_i} - p_i - V^{NHI}, h^{s_i} + \Delta h_i)] + (1 - \pi) u(y^w - V^{NHI}, h^w) = EU$$

where EU, expected utility absent medical technology, is defined as

$$EU = \sum_{i=1}^{N} [\pi_i u(y^{s_i}, h^{s_i})] + (1 - \pi) u(y^w, h^w)$$

The ex ante willingness to pay "with health insurance" is implicitly defined as

$$\sum_{i=1}^{N} \left[\pi_i u \left(y^{s_i} - \sum_{j=1}^{N} \pi_j \bar{p}(p_j) - V^{WHI}, h^{s_i} + \Delta h_i \right) \right] + (1 - \pi) u \left(y^w - \sum_{j=1}^{N} \pi_j \bar{p}(p_j) - V^{WHI}, h^w \right) = EU$$

When $N = 1$, we have $(1 - \pi) = 1 - \pi_1$ and all of the above expressions simplify to the two-state case presented in the main text.

We solve for V_C, V^{NHI}, and V^{WHI} using standard numerical methods. The insurance value is equal to the incremental willingness to pay when accounting for risk: $V_I = V^{NHI} - V_C$. Financial spending risk is equal to the incremental willingness to pay when an individual gains access to financial insurance markets: $V_{I_F} = V^{WHI} - V^{NHI}$. The physical insurance value can then be easily computed as $V_{I_P} = V_I + V_{I_F}$.

B. Employing certainty equivalents

Define a certainty equivalent as the maximum amount that a consumer is willing to pay to completely insure against risk. For an individual without access to medical technology or financial insurance markets, the certainty equivalent, CE_0, is defined implicitly as:

$$u(y^w - CE_0, h^w) = \pi u(y^s, h^s) + (1-\pi)u(y^w, h^w)$$

Following the introduction of a new medical technology that generates positive consumer surplus, the certainty equivalent, $CE_1 < CE_0$, is defined implicitly as:

$$u(y^w - CE_1, h^w) = \pi u(y^s - p, h^s + \Delta h) + (1-\pi)u(y^w, h^w)$$

The new medical technology reduces the certainty equivalent for two distinct reasons. First, the new technology generates consumer surplus for sick individuals. This is what we call the "conventional value" of technology. Second, the technology generates what we call "insurance value" because the consumer now faces less risk. Note that the first source of value comes from a reduction in the mean and the second comes from a reduction in the variance.

Finally, consider the case where the consumer has access to fee-for-service health insurance. The certainty equivalent, CE_2, is now defined implicitly as:

$$u(y^w - CE_2, h^w) = \pi u(y^s - p + (1-\pi)p, h^s + \Delta h) + (1-\pi)u(y^w - \pi p, h^w)$$

The conventional value (V_C), net insurance value (V_I) and financial spending risk (V_{I_F}) associated with a new technology are equal to the incremental reductions in uncertainty associated with the introduction of the technology and the availability of health care insurance:

$$V_C + V_I = CE_0 - CE_1$$

$$V_{I_F} = CE_1 - CE_2$$

The physical insurance value can then be defined as $V_{I_P} = V_I + V_{I_F}$. A shortcoming of employing certainty equivalents is that it does not separately identify V_C (a mean shift) and I_V (a variance shift). This is not a problem for most studies that value insurance because the mean shifts are typically already measured in dollars. For example, Finkelstein and McKnight (2008) subtract out changes in mean medical spending following the introduction of Medicare so that their welfare estimates can be attributed solely to risk reduction. We cannot do that in our setting because changes in health, unlike changes in medical spending, are not measured in dollars.

One might be tempted to estimate V_C using the willingness to pay method we present in the main text. Doing so can generate nonsensical estimates, however, because willingness to pay is calculated from the perspective of the sick state while certainty equivalents are always calculated from the healthy state, and those states employ different marginal utilities of income. For example, it is possible to generate scenarios where the insurance value is negative even though a consumer has positive demand for health insurance in the sick state. Nevertheless, we obtain similar results overall if we estimate our model using certainty equivalents rather than the willingness to pay method we present in the main text.

C. Robustness checks

Appendix Table 9 and Appendix Table 10 display aggregate estimates for the hypothetical health increased considered in the main text when we incorporate price. We follow Philipson and Jena (2006)

and assume that the price of medical technology is equal to 20% of the ex post surplus it generates. For the sake of brevity we present results only for Scenario 2, where all health gains are concentrated in the two poorest health states.

Comparing Appendix Table 9 to Table 4 shows that incorporating price lowers the full willingness to pay, as expected. This is because the conventional value is lower (there is less ex post surplus) and because the consumer is now exposed to financial risk. The magnitude of financial risk increases with age because price, a set fraction of ex post surplus, also increases with age.

Appendix Table 10 reports the per capita lifetime value of the health gains. Even after accounting for the negative financial spending risk associated with purchasing medical technology, the total value still significantly exceeds the conventional value.

Appendix Table 11 show that the estimates of insurance value presented in Table 7 increase greatly in magnitude if we assume that income in the sick state is equal to $60,000 rather than $120,000.

D. Data appendix

Each study in the CEAR database is categorized into one of 70 possible disease classifications, e.g., "tuberculosis" or "endocrine disorders". We mapped each of these verbal classifications into corresponding ranges of ICD-9-CM codes.[27] For example, tuberculosis corresponds to the codes 10 through 18.

Some CEAR disease classifications were calculated by excluding subcategories from a larger category. For example, the CEAR database classifications include four types of respiratory diseases: "Asthma", "COPD", "Respiratory Infections", and "Other Respiratory". These are all subcategories of "Diseases of the Respiratory System" (codes 460-519). We therefore assigned to "Other Respiratory" all respiratory system codes that were not included in the definitions of "Asthma", "COPD", and "Respiratory Infections".

We then estimated the incidence of each disease category using the 1996 – 2010 Medical Expenditure Panel Surveys (MEPS). These surveys report the ICD-9 codes corresponding to every condition suffered by a respondent during the two years she was surveyed. We mapped these codes into the disease categories given by Appendix Table 12. Next, for each panel and disease category, we calculated (1) the number of respondents who contracted the disease in the second year of the panel, and (2) the number of respondents at risk for the disease in the first year of the panel. We then pooled the panels together and divided (1) by (2) to obtain our incidence estimates. Appendix Table 12 shows our results.

[27] See ftp://ftp.cdc.gov/pub/Health_Statistics/NCHS/Publications/ICD9-CM/2008/Dtab09.zip.

TABLES AND FIGURES

Table 2. Average health status for selected quantiles, by age group and gender.

		Quantiles								
Group	**Observations**	**10**	**20**	**30**	**40**	**50**	**60**	**70**	**80**	**90**
Males (18-34)	11,382	0.726	0.796	0.886	1	1	1	1	1	1
Males (35-49)	11,424	0.681	0.743	0.796	0.835	1	1	1	1	1
Males (50-64)	7,998	0.62	0.691	0.74	0.796	0.796	1	1	1	1
Males (65-79)	4,344	0.569	0.681	0.704	0.727	0.796	0.796	0.962	1	1
Males (80+)	1,120	0.208	0.56	0.638	0.699	0.725	0.761	0.796	0.916	1
Females (18-34)	13,049	0.717	0.787	0.835	0.895	1	1	1	1	1
Females (35-49)	13,351	0.62	0.725	0.787	0.8	0.857	1	1	1	1
Females (50-64)	9,210	0.534	0.689	0.725	0.761	0.796	0.826	1	1	1
Females (65-79)	5,567	0.332	0.62	0.691	0.721	0.743	0.796	0.814	0.971	1
Females (80+)	2,077	0.116	0.427	0.62	0.681	0.696	0.731	0.796	0.844	1

Notes: Table presents pooled, weighted estimates from the 2000-2003 MEPS. Each cell represents the average EQ-5D index for that quantile and group. The EQ-5D index is a measure of quality of life that ranges from 0 (poor health) to 1 (perfect health).

Table 3. Value of a health improvement that is distributed evenly across all health states.

Group	**Conventional**	**Insurance**	**Total**
Males (18-34)	$5,290	$1,344	$6,634
Males (35-49)	$7,368	$1,791	$9,160
Males (50-64)	$9,634	$2,145	$11,779
Males (65-79)	$12,984	$1,738	$14,721
Males (80+)	$18,912	$11,292	$30,204
Females (18-34)	$7,007	$1,399	$8,406
Females (35-49)	$9,325	$1,943	$11,269
Females (50-64)	$11,762	$2,280	$14,042
Females (65-79)	$16,135	$4,472	$20,607
Females (80+)	$22,156	$27,351	$49,507

Notes: This table displays the value of a modest hypothetical increase in quality of life that is distributed evenly across all potential health states, for an individual facing the health risk profile displayed in Table 2. It assumes there is no spending risk, so calculated insurance values consist solely of physical insurance value.

Table 4. Value of a health improvement that is concentrated in the two lowest health states.

Group	Conventional	Insurance	Total
Males (18-34)	$5,261	$1,852	$7,114
Males (35-49)	$7,048	$2,774	$9,822
Males (50-64)	$8,935	$4,056	$12,991
Males (65-79)	$11,447	$5,503	$16,950
Males (80+)	$17,369	$35,674	$53,044
Females (18-34)	$6,751	$2,336	$9,087
Females (35-49)	$8,781	$4,044	$12,825
Females (50-64)	$10,765	$6,082	$16,847
Females (65-79)	$14,867	$17,780	$32,647
Females (80+)	$19,931	$60,776	$80,708

Notes: This table displays the value of a modest hypothetical increase in quality of life that is concentrated in the two poorest health states, for an individual facing the health risk profile displayed in Table 2. It assumes there is no spending risk, so calculated insurance values consist solely of physical insurance value.

Table 5. Aggregate lifetime value of the health improvements from Table 3 and Table 4.

	Health gains evenly distributed				Health gains concentrated among sick			
Gender	Conventional	Insurance	Total	Fraction insurance	Conventional	Insurance	Total	Fraction insurance
Male	$220,507	$59,410	$279,917	0.27	$209,077	$123,891	$332,969	0.59
Female	$285,047	$92,088	$377,135	0.32	$266,898	$217,437	$484,335	0.81

Notes: Estimates are weighted to reflect discounting and survival probabilities. The analysis assumes there is no spending risk, so calculated insurance values consist solely of physical insurance value.

Table 6. Summary statistics for the sample of therapeutic medical innovations from CEAR.

	Mean	SD	Min	Max
Horizon (years)	56.74	35.12	1	85
QALY discount rate	0.033	0.009	0.015	0.06
Cost discount rate	0.035	0.009	0.015	0.06
Health status in sick state (QALYs)	0.714	0.145	0.103	0.995
Δh (QALYs)	0.031	0.050	0.000	0.468
P (2011 dollars)	$1,942	$8,815	$0	$162,583
Probability of disease x 100	4.090	3.985	0.007	17.301

Notes: Sample consists of 1,797 interventions. Δh and P correspond to the health improvement and price of a medical technology.

Table 7. Means and percentiles of the conventional and insurance values of technologies in CEAR for different values of risk aversion.

				Insurance value					
	Conventional			Physical insurance			Financial spending risk		
σ (R^c)	Median	90th percentile	Mean	Median	90th percentile	Mean	Median	90th percentile	Mean
0.5 (0.85)	$213.14	$2,324.56	$768.69	($4.43)	$47.24	$7.23	($1.17)	($0.06)	($1.54)
1 (1)	$213.14	$2,324.56	$768.69	$3.73	$338.89	$133.50	$0.01	$1.47	$5.53
3 (1.6)	$213.14	$2,324.56	$768.69	$84.43	$2,497.94	$883.06	$6.42	$99.02	$45.22
5 (2.2)	$213.14	$2,324.56	$768.69	$187.57	$5,442.03	$1,893.65	$15.49	$232.45	$104.57
8 (3.1)	$213.14	$2,324.56	$768.69	$403.66	$11,533.12	$3,495.98	$32.99	$545.41	$224.46

Notes: Units are 2011 dollars. Sample is 1,797 interventions from CEAR. Estimates are weighted by the prevalence of disease. The parameter σ affects the curvature of the utility function. R^c is the implied coefficient of relative risk aversion over consumption.

Table 8. Means and percentiles of the insurance values of technologies in CEAR, as a fraction of the conventional value.

	Physical insurance			Financial spending risk			Total insurance value		
σ (R^c)	Median	90th percentile	Mean	Median	90th percentile	Mean	Median	90th percentile	Mean
0.5 (0.85)	-0.02	0.02	0.01	-0.01	0.00	0.00	-0.02	0.02	0.01
1 (1)	0.02	0.15	0.17	0.00	0.00	0.01	0.02	0.15	0.17
3 (1.6)	0.40	1.07	1.15	0.03	0.04	0.06	0.37	1.03	1.09
5 (2.2)	0.88	2.34	2.46	0.07	0.10	0.14	0.81	2.24	2.33
8 (3.1)	1.89	4.96	4.55	0.15	0.23	0.29	1.74	4.73	4.26

Notes: Units are 2011 dollars. Sample is 1,797 interventions from CEAR. Estimates are weighted by the prevalence of disease. The parameter σ affects the curvature of the utility function. R^c is the implied coefficient of relative risk aversion over consumption.

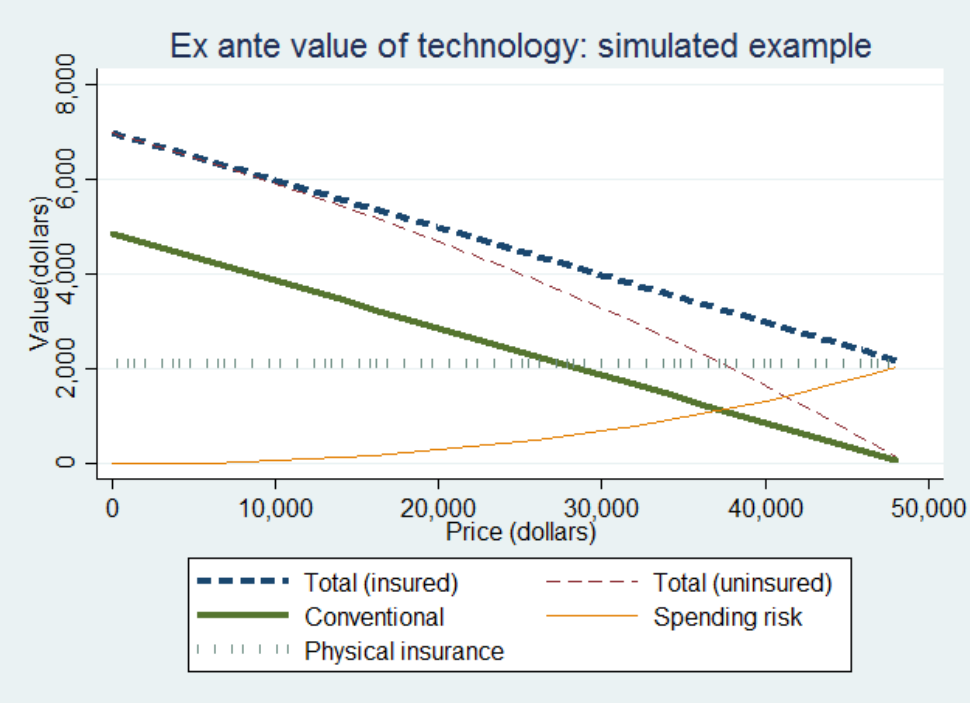

Figure 1. Simulated estimates of the different components of the value of medical technology as a function of price. "Total (insured)" is equal to "conventional" plus "physical insurance". "Total (uninsured)" is equal to "conventional" plus "physical insurance" minus "spending risk". Simulation parameters are $\gamma = 0.3, \sigma = 3, \pi = 0.1, y^w = y^s = \$120,000, h^w = 1, h^s = 0.8$, and $\Delta h = 0.2$.

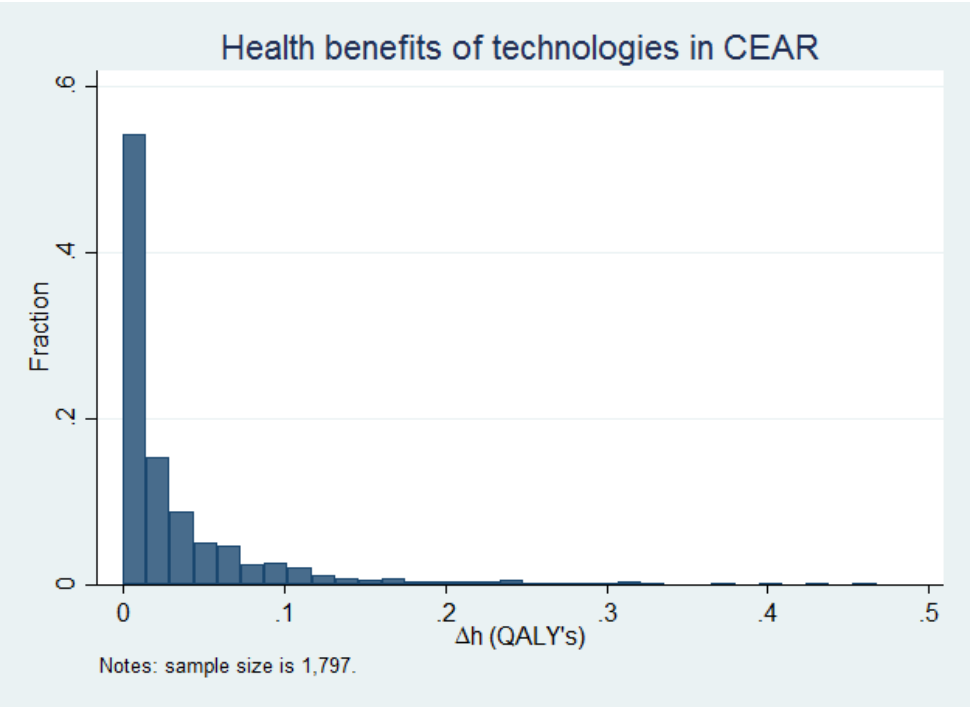

Figure 2. This figure displays the distribution of Δh, a measure of health improvement that ranges from 0 to 1, in our sample of therapeutic innovations from CEAR.

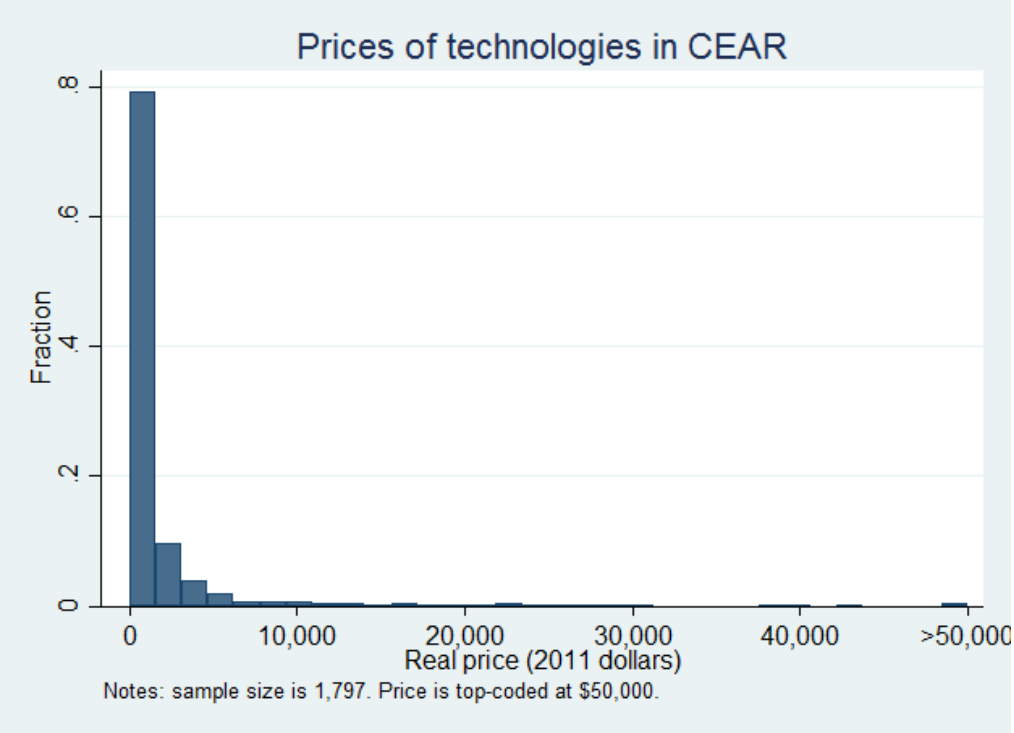

Figure 3. This figure displays the distribution of prices for the treatments in our sample of therapeutic innovations from CEAR. Price is top-coded at $50,000 for display purposes.

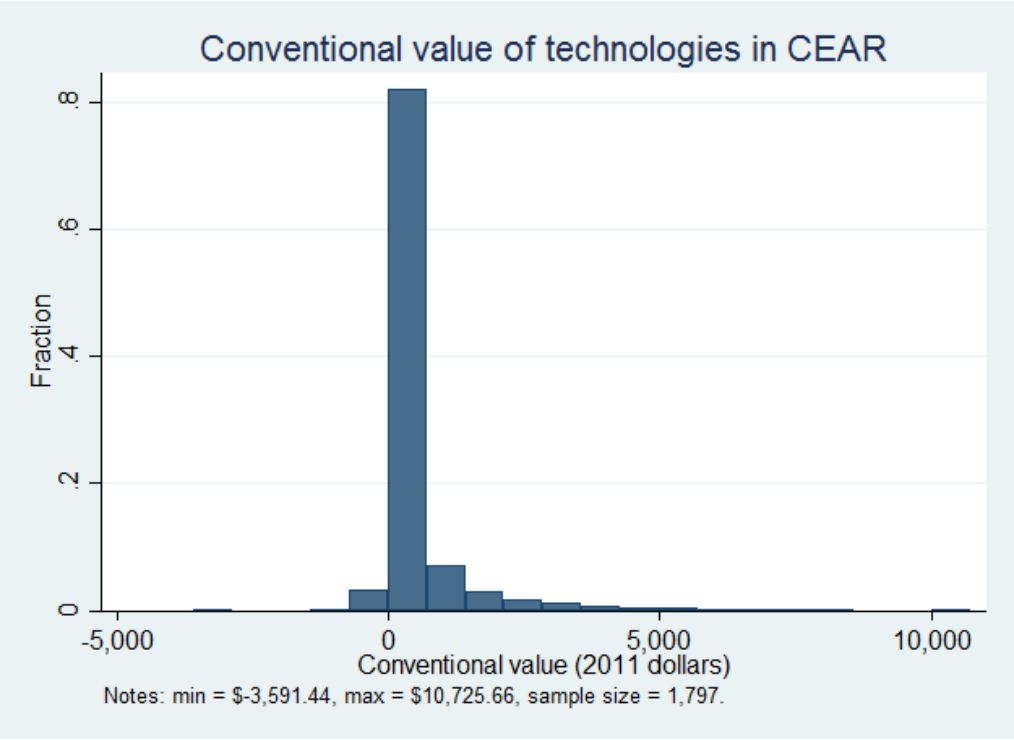

Figure 4. Distribution of the calculated conventional value of therapeutic technologies in CEAR. Most treatments generate little value.

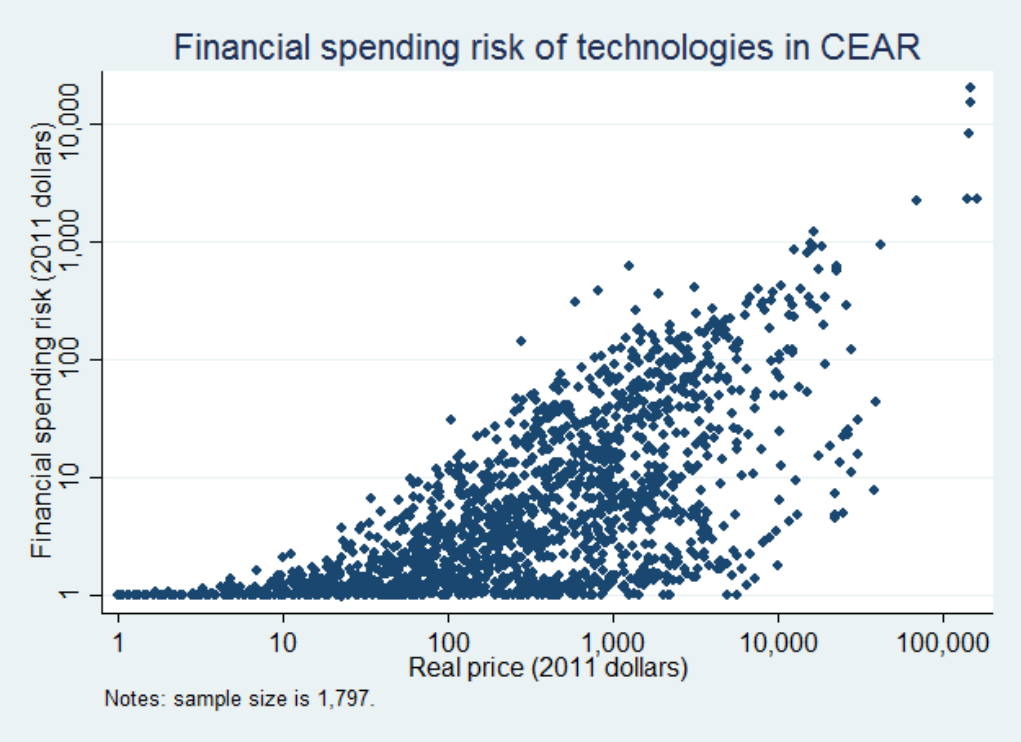

Figure 5. This graph shows the calculated financial spending risk of each therapeutic medical innovations in CEAR as a function of their price. Risks are displayed as positive values, and are exactly equal to the coverage value of an actuarially fair, perfect fee-for-service health insurance policy.

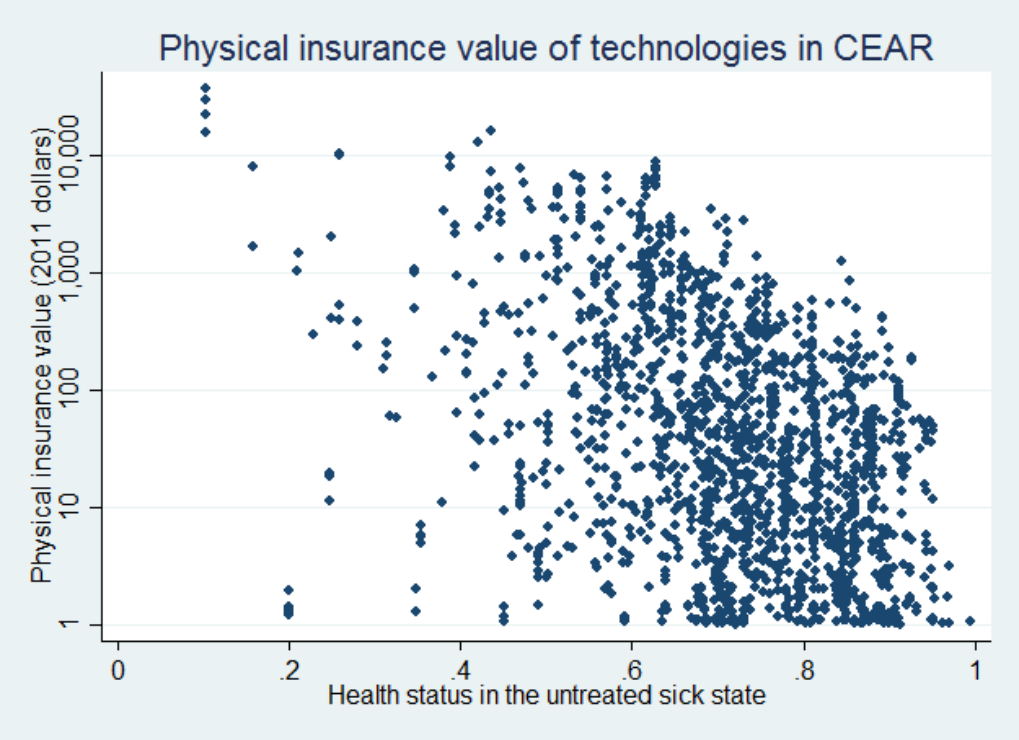

Figure 6. This graph shows the calculated physical insurance value of the therapeutic medical innovations in CEAR as a function of the patient's health status.

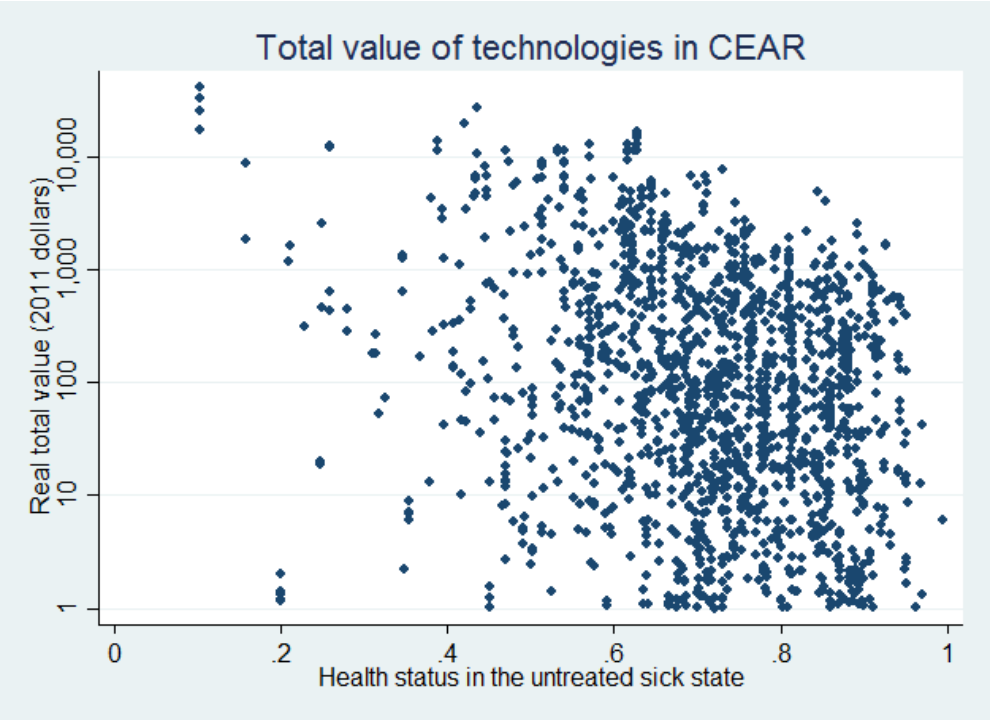

Figure 7. This graph shows the total value of the therapeutic technologies in CEAR as a function of the health status of the patient in the untreated sick state. The total value is calculated assuming the patient has access to health care insurance. The figure omits technologies with negative conventional value.

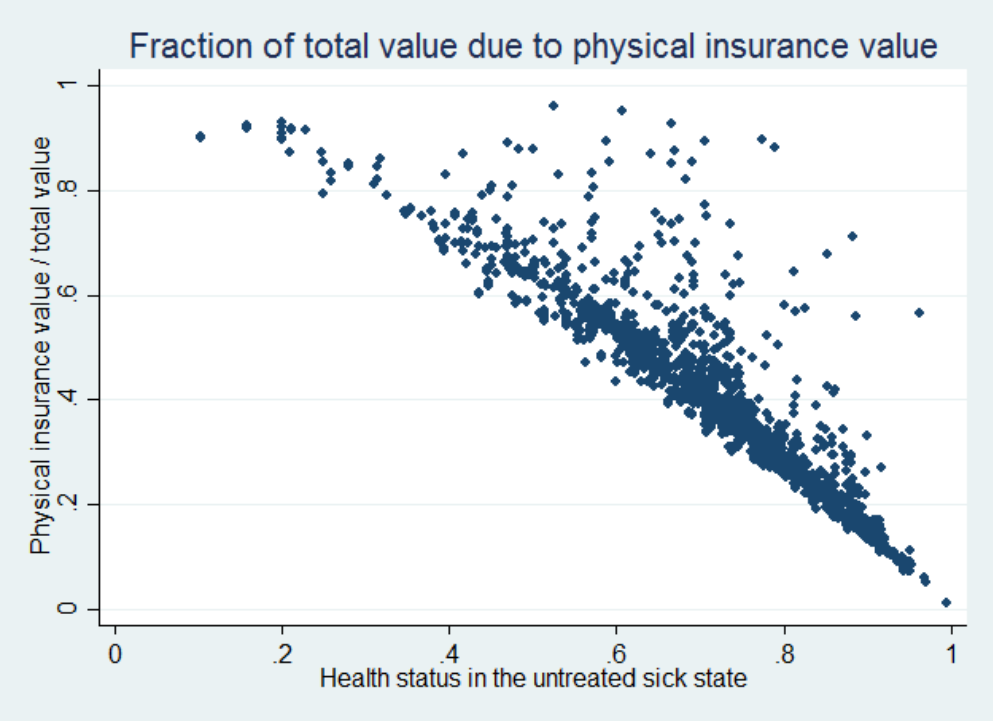

Figure 8. Treatments for diseases with low health status (high unmet need) generate most of their value from insurance value. The total value is calculated assuming the patient has access to health care insurance. Source: CEAR.

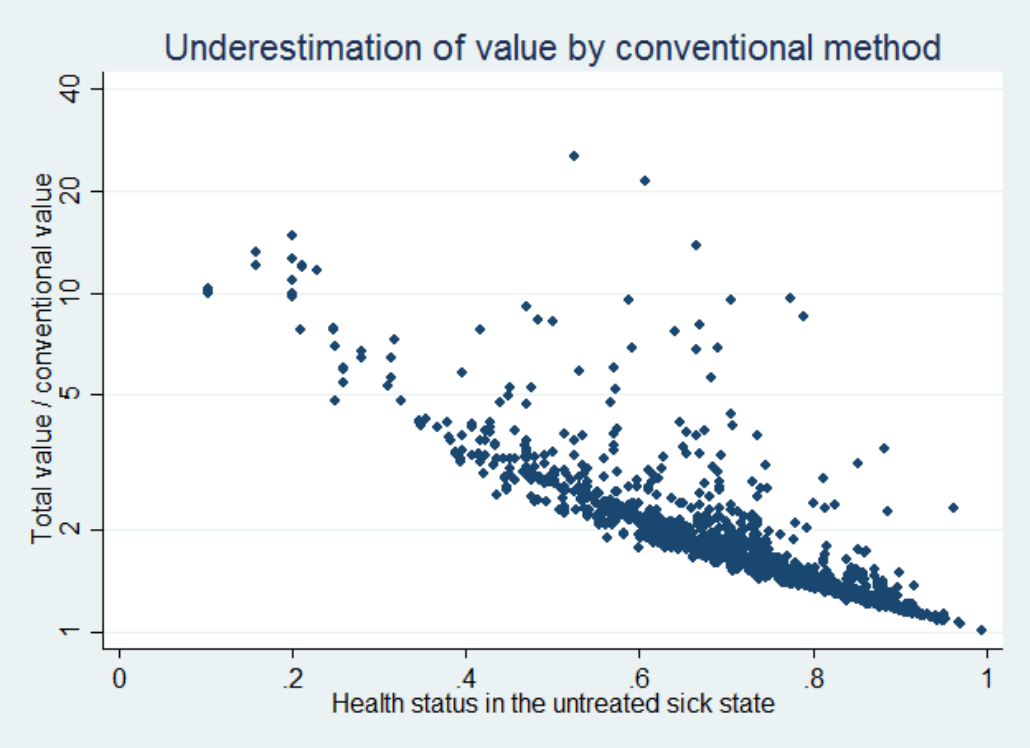

Figure 9. The conventional valuation of medical technology significantly underestimates the total value of treatments for individuals with high "unmet need", i.e., treatments for individuals with low health status. This figure omits technologies with negative conventional value and calculates total value assuming the patient has access to health care insurance. Source: CEAR.

APPENDIX TABLES

Table 9. Value of health improvements that are concentrated in the two poorest health states, when the price of medical technology is equal to 20% of ex post willingness to pay.

		Insurance value		
Group	**Conventional**	**Physical**	**Financial**	**Total**
Males (18-34)	$4,209	$1,852	$233	$5,829
Males (35-49)	$5,638	$2,774	$296	$8,116
Males (50-64)	$7,148	$4,056	$368	$10,836
Males (65-79)	$9,158	$5,503	$316	$14,345
Males (80+)	$13,895	$35,674	$3,039	$46,531
Females (18-34)	$5,401	$2,336	$236	$7,501
Females (35-49)	$7,025	$4,044	$377	$10,692
Females (50-64)	$8,612	$6,082	$496	$14,199
Females (65-79)	$11,894	$17,780	$1,466	$28,208
Females (80+)	$15,945	$60,776	$5,927	$70,795

Notes: This table displays the value of a modest hypothetical increase in quality of life that is concentrated in the two poorest health states, for an individual facing the health risk profile displayed in Table 2. The total value is equal to the conventional value plus the physical insurance value minus the financial spending risk.

Table 10. Aggregate lifetime value of health improvements that are concentrated in the two poorest health states, when price is set equal to 20% of ex post willingness to pay.

		Insurance value		Total value	
Gender	**Conventional**	**Physical**	**Financial**	**Uninsured**	**Insured**
Male	$167,262	$123,891	$11,703	$279,450	$291,153
Female	$213,518	$217,437	$20,045	$410,910	$430,955

Notes: Estimates are weighted to reflect discounting and survival probabilities. Total values are calculated assuming (1) consumer is uninsured and (2) consumer is insured, i.e., has access to health insurance.

Table 11. Means and percentiles of the conventional and insurance values of technologies in CEAR for different values of risk aversion under the alternative assumption that income in the sick state equals $60,000 instead of $120,000.

				Insurance value					
	Conventional			Physical insurance			Financial spending risk		
σ (R^c)	Median	90th percentile	Mean	Median	90th percentile	Mean	Median	90th percentile	Mean
0.5 (0.85)	$91.94	$1,072.92	$355.10	$75.42	$863.47	$284.69	$9.48	$94.59	$40.45
1 (1)	$91.94	$1,072.92	$355.10	$117.73	$1,386.55	$451.19	$15.14	$157.88	$62.44
3 (1.6)	$91.94	$1,072.92	$355.10	$320.99	$4,530.73	$1,398.80	$42.49	$530.67	$197.22
5 (2.2)	$91.94	$1,072.92	$355.10	$625.67	$8,396.28	$2,466.85	$79.04	$1,037.51	$399.97
8 (3.1)	$91.94	$1,072.92	$355.10	$1,080.65	$12,347.83	$3,650.35	$131.14	$1,697.48	$711.74

Notes: Units are 2011 dollars. Sample is 1,797 interventions from CEAR. Estimates are weighted by the prevalence of disease. The parameter σ affects the curvature of the utility function. R^c is the implied coefficient of relative risk aversion over consumption.

Table 12. Annual prevalence for the disease categories listed in CEAR, as estimated using MEPS.

CEAR disease classification	Probability x 100	CEAR observations
Alzheimer's and Other Dementias	0.130	20
Asthma	1.082	3
Breast Cancer	0.089	88
COPD	2.056	15
Cardiovascular Diseases	3.195	170
Cerebrovascular Disease	0.420	30
Colorectal Cancer	0.052	4
Congenital Anomalies	0.269	4
Depression and Bipolar Affective Disorder	0.154	2
Diabetes Mellitus	0.620	41
Digestive Diseases	6.538	54
Endocrine Disorders	3.276	52
Genito-Urinary Diseases	4.337	40
HIV/AIDS	0.007	52
Hearing	3.275	7
Hematologic Cancers	0.058	31
Hematology - Other	0.146	28
Hypertension	2.167	26
Infectious	10.733	186
Injuries/Exposures	10.852	11
Ischaemic Heart Disease	0.512	65
Kidney Disease	0.071	25
Lipids	0.243	17
Lung Cancer	0.057	10
Malignant Neoplasms	1.041	142
Maternal and Child Health	0.553	6
Multiple Sclerosis	0.019	23
Musculoskeletal and Rheumatologic	7.996	201
Neuro-Psychiatric and Neurological	5.120	34
Non-Cancer Prostate Disease	0.318	6
Non-Ischaemic Heart Disease	0.955	53
Osteoarthritis	0.497	4
Other	11.400	31
Other Endocrine	3.217	9
Other Genito-Urinary	4.034	2
Other Infectious Diseases	9.822	39
Other Musculoskeletal	6.478	38

Other Neoplasms	1.696	14
Other Neuro-Psychiatric and Neurological	4.904	5
Other Non-Infectious GI Diseases	6.443	26
Other Respiratory	1.981	12
Ovary Cancer	0.007	4
Parkinson Disease	0.031	3
Peptic Ulcer Disease	0.152	2
Prostate Cancer	0.106	15
Respiratory Diseases	17.301	13
Respiratory Infections	15.130	2
Rheumatoid Arthritis	0.141	21
STDs excluding HIV	1.305	1
Schizophrenia	0.029	3
Seizure Disorders (Epilepsy)	0.032	10
Sense Organ Diseases	6.806	4
Skin Diseases (Non-Cancer)	4.614	7
Substance Abuse Disorders	0.213	6
Tuberculosis	0.020	4
Vascular, Non-Cardiac, Non-Cerebral	1.030	30
Vision	4.021	46
Total		**1,797**

Source: 1996-2010 MEPS surveys.