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# The Insurance Value of Medical Innovation

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**Abstract**. Technological change in health care is often viewed as a major contributor to increased financial risk, since new technologies are often more expensive than old ones. While true in a static sense, this viewpoint overlooks the manner in which medical innovations reduce the health risk borne by consumers. First, using the parlance of Ehrlich and Becker (1972), therapeutic technologies serve as "self-insurance" that lowers the impact of illness and preventative technologies serve as "self-protection" that lowers the probability of illness. Second, given the incompleteness of real-world financial markets, medical technologies improve the performance of health insurance markets ("market insurance") that transfer wealth across morbidity states. We show that standard methods of valuing medical technologies overlook these insurance benefits from technology. As a result, standard approaches may underestimate the value of medical technology that improves quality of life, and may under or overestimate the value of preventive technologies. Using data from the Tufts Cost-Effectiveness Registry, we estimate total insurance value for a range of real-world medical technologies. We estimate that this insurance value adds 113% to the traditional valuation. Moreover, for typical levels of risk aversion, the insurance value of technology is significantly larger than the insurance value of health insurance itself.

# INTRODUCTION

Medical innovation is frequently pinpointed as the primary driver for the rising cost of health insurance (Altman and Blendon 1977, LaCronique and Sandier 1981, Showstack, Stone et al. 1985, Wilensky 1990, Newhouse 1992, Zweifel, Felder et al. 1999, Okunade and Murthy 2002, Chandra and Skinner 2012). As a result, health policymakers often think about innovation as expanding the total quantity of risk that must be insured by the health insurance system (Weisbrod 1991). While this argument is correct in a static, *ex post* sense, it overlooks the fundamental role played by medical innovation in reducing physical risks to life and health.

Only medical technology can reduce or eliminate physical risks. Real-world financial health insurance cannot directly reduce these risks; it merely pays for the purchase of medical technology. While one can imagine pure indemnity health insurance that pays a consumer to compensate them for the occurrence of illness, this type of insurance is not observed in practice due to a variety of market failures, such as the difficulty of writing complete contracts that specify payments as a function of illness and its severity. In a world of incomplete health insurance contracts, the advent of a valuable new medical treatment converts the uninsurable physical risk of illness into the insurable financial risk associated with the cost of purchasing the new treatment.[1]

Against the backdrop of an insurance market that imperfectly eliminates health-related risks, new medical treatments can function as a second-best source of insurance value, for at least two reasons. First, because health insurance pays for the cost of medical treatments rather than the cost of illness itself, health insurance markets require the arrival of medical innovations to facilitate the transfer of resources from the healthy state to the sick state. In other words, therapeutic medical technology enables the expansion of "market insurance" as defined by Isaac Ehrlich and Gary Becker (1972) . We call this the "market-insurability value" of therapeutic technology. Second, therapeutic technology reduces the cost borne by an individual who falls ill so long as its price leaves the consumer some surplus. This value is analogous to "self-insurance" as defined by Ehrlich and Becker because it reduces the loss suffered in the sick state. Both these sources of value accrue above and beyond the standard notion of *ex post* consumer surplus that would accrue if medical technology functioned like other goods without risky demands.

A simple example helps make this clear. Think of an HIV-negative consumer facing the risk of contracting HIV in the years before the discovery of effective treatments for the disease. In the absence of a treatment, this consumer cannot insure herself against the risk of HIV, in the sense of transferring resources to the sick state. Insurers are unwilling to sell pure indemnity insurance contracts that make payments to consumers conditional on the occurrence of illness alone. As a result, this consumer has to bear the full risk of HIV herself.

Now consider the introduction of new technologies such as highly active antiretroviral treatment (HAART). Since these technologies are not priced to extract all surplus (Philipson and Jena 2006), they are valuable even to a sick consumer paying out of pocket for them. This is the standard "*ex post* consumer surplus" that would be generated by the purchase of any valuable good, like bananas, butter, or minivans.

[1] Philipson and Zanjani (2013) make a related point in a paper written independently of and at the same time as this one. They focus on what we call the "self-insurance value" of technology, and the implications this has for the function of medical research and development expenditures as health *stock* insurance. In contrast, we focus on the interaction between medical technology and financial health insurance, and we identify the important case of prevention, which may under certain circumstances exhibit zero or even negative risk-reduction value. In addition, we focus on quantifying empirically the distinct welfare contributions of medical technology and health insurance.

Yet, there is additional value that derives from the riskiness of illness. First, because HAART generates *ex post* consumer surplus, it also lowers the cost of being HIV+, and thus compresses the spread in utilities between the sick and healthy states. This is valuable *ex ante* to the consumer, as "self-insurance" for a risk-averse consumer who dislikes mean-preserving spreads of consumption.

Second, the consumer can now seek health insurance that covers the cost of these technologies in the event of illness. This enables the consumer to transfer resources from the healthy to the sick state and thus makes the risk of HIV partially insurable in the financial markets. This generates "market-insurability" value. For both these reasons, even though HAART raises the cost of financial insurance, it lowers the total amount of risk borne by the consumer herself. The value of this risk-reduction is over and above the *ex post* consumer surplus enjoyed by a patient who already has HIV.

The market-insurability and self-insurance functions of innovation have implications for how economists value medical innovation. First, prior theoretical and empirical methods may underestimate the value of innovation, and its distributional impacts. Typically, medical innovation is treated like a standard good without risky demand and valued solely according to the *ex post* consumer and producer surplus it generates. The *ex post* consumer surplus alone can be quite valuable for some technologies (see, e.g., Philipson and Jena 2006), but failing to incorporate the *ex ante* market-insurability and self-insurance values may lead analysts to understate the total value of more marginal technologies, or to mischaracterize the distributional effects of all medical technologies when risk aversion varies across groups in the population. More generally, insufficient attention has been paid to identifying and separating the *ex ante* and *ex post* values of technology. This makes it hard to compare alternative estimation approaches, which often produce widely variable estimates of value.

Second, prior literature has tended to overstate the role of financial health insurance in health risk-reduction, and correspondingly to understate (or even mischaracterize) the role of medical technology. The literature has tended to view medical technology as risky, because it generates additional financial risk, and to view health insurance as the antidote to this additional risk. A better way to compare the insurance values from medical technology and health insurance is to decompose insurance into market insurance and self-insurance as Ehrlich and Becker do. Both medical technology and health insurance are necessary ingredients in a market insurance contract: because health insurance merely pays for medical technology, it has no value without technology. Moreover, medical technology, if priced to leave consumers some surplus, also provides self-insurance. Thus, technology may be viewed as qualitatively contributing more to total insurance value than does health insurance itself. Indeed, the lower is the price of medical technology, the greater is the self-insurance value from medical technology, and the less is the insurance contribution of financial health insurance itself.[2]

Technology that prevents sickness or reduces the probability of death can also be analyzed through this prism. The important difference is that risk-averse individuals primarily observe changes in terms of trade in health insurance and other financial products as a result of such technology. Preventive technology makes health insurance more affordable – i.e., the cost of transferring a dollar to the sick state – by lowering the probability of sick. None of these effects are accounted for in the standard valuations of preventative technology. Moreover, these technologies have implications for the relative value of financial products for risk-averse consumers.

In this paper we provide a theoretical model that formalizes the observations above. Moreover, we use cost and benefits data on a sample of medical technologies in the Cost-Effectiveness Analysis Registry to estimate

[2] Under this view, health insurance expansions may not increase the insurance value from health insurance relative to technology. The expansion has no value without – and certainly more value with – medical technology to pay for. It is not obvious how to allocate credit for insurance value from the expansion between health insurance and technology.

and contextualize the value of therapeutic technologies. Specifically, we estimate (1) the self-insurance value of each technology and (2) market insurability value of technology and compare them to (3) the standard consumer surplus value of each technology. We find that the total insurance value of technology exceeds the standard consumer surplus value by 113%. We also find that risk-averse consumers value preventive technology more than risk-neutral consumers.

Our theoretical analysis has implications for the economic relationship between medical innovation and health insurance. The existing literature has observed that health insurance can drive medical innovation (Goddeeris 1984, Newhouse 1992).[3] It is also known that high-priced technology drives demand for health insurance. Coupling this with the observation that health insurance only pays for medical technology implies that the two products are price complements on the extensive margin of innovation.[4] That is, a reduction in technology price that induces purchase of medical treatment increases the quantity of insurance purchased (Weisbrod 1991). Less well-appreciated is the point that technology and insurance are price substitutes on the intensive margin. For a consumer that purchases medical technology when she falls ill, lowering the price of that technology increases its self-insurance value and consequently reduces the value of formal health insurance. Because self-insurance and market insurance are substitute forms of insurance, reducing the price of technology reduces the quantity of health insurance purchased.

Finally, our analysis has implications for the literature on the allocation of economic rents between health care providers and health insurers. Lakdawalla and Yin (2012) note the importance of health insurance concentration on pricing and thus allocation of rents among the two. This paper has implications for the range over which innovative providers and insurers may bargain over prices. An innovator's threat point is the value of innovation without insurance while an insurer's threat point is the value of insurance without innovation. The former is greater than the latter because insurance for an innovation has no value without that innovation, but not vice versa.

The remainder of this paper has the following outline. Section I describes the market-insurability value and the self-insurance value of therapeutic innovation to a risk-averse individual. Section II characterizes the insurance value of preventive technology that accrues to a risk-averse individual, but not a risk-neutral one. Section III provides empirical estimates of market-insurability value and self-insurance value of therapeutic technologies and compares them to the *ex post* consumer surplus from technology and the insurance value of health insurance. It then goes on to quantify the the effect of risk aversion on the value of preventive technology.

## I: THE VALUE OF THERAPEUTIC MEDICAL TREATMENTS

Consider an individual who faces a health risk. We are interested in analyzing the value of a new medical technology that treats this health risk and is cheap enough to improve consumer welfare. Thus, we focus on technologies that generate non-negative consumer surplus even in the absence of health insurance. In this section, we focus on treatment technologies that reduce morbidity. Later, we study preventative technologies that reduce morbidity.

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[3] In general, health insurance is treated as an outward shift in the demand for medical technology. See, e.g., Acemoglu et al. (2006), Blume-Kohout and Sood (2008), Clemens (2012). However, Malani and Philipson (2013) also observe that health insurance can reduce the supply of human subjects for the clinical trials required for medical innovation.

[4] Lakdawalla and Sood (2013) demonstrate that health insurance and medical innovation are complementary in the sense that health insurance reduced the static inefficiency from patents and thus reduces the cost of using patents to incentivize innovation.

We first quantify the value of the treatment if the patient does not face consumption risk due to illness and the cost of medical care because she has indemnity insurance. We define this as the "risk-free value of treatment" and show that it is similar – but not identical – to standard methods for valuing medical technology. We then explain the difference between the risk free value of treatment and standard method of valuing treatment.

An important distinction is that indemnity insurance markets are incomplete and so consumers bear some residual financial risk due to illness. We characterize the additional value that accrues from medical treatments in this context. We define this as the "insurance value of treatment" and show that it is not incorporated into standard methods of valuing the willingness-to-pay for medical technology. We decompose this insurance value into two components: (1) the value created when treatment reduces the cost of being sick, which we call "the self-insurance value of treatment;" and (2) the value created when treatment expands possibilities for health insurance, which we call "the market-insurability value of treatment."

## A: The risk-free value of therapeutic technology

The individual derives utility from non-health consumption and from health according to $u(c, h)$. She is either sick or well, and she falls sick with probability $\pi$. 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 $y^s$ when sick. Finally, she can purchase as much indemnity insurance as she wishes in a perfectly competitive marketplace. She can choose to transfer $\tau$ units of consumption away from the healthy state, and will receive the actuarially fair transfer $[(1-\pi)/\pi]\tau$ when sick.

In the absence of medical treatment, the individual's optimization problem is:

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

The consumer's solution equates the marginal utility of wealth across states:

$$(1-\pi)\left[u_c\left(y^s + \frac{1-\pi}{\pi}\tilde{\tau}, h^s\right) - u_c(y^w - \tilde{\tau}, h^w)\right] = 0 \tag{1}$$

where subscripts indicate partial derivatives, superscripts indicate the health state, and $\tilde{\tau}$ is the optimal transfer across states. Note that equal marginal utilities need not imply equal consumption across states, except in the special case where $u_{ch} = 0$, i.e., state-independent utility.

We now introduce a medical treatment into this perfectly insured and riskless setting. Suppose the individual can purchase a technology that promises a marginal increase in health of $\Delta h$ in the sick state at a marginal price of $p$. Applying the envelope theorem allows us to compute the optimal transfers across states when consumption falls by $p$ and health rises to $h^s + \Delta h$.

To simplify the notation, denote by $\tilde{u}_j^i$ the marginal utilities of good $j \in \{c, h\}$ in state $i \in \{s, w\}$ under the assumption of complete indemnity markets. The change in utility due to technology is $\pi[\tilde{u}_h^s d\Delta - \tilde{u}_c^s dp]$. The total social value of the new technology is given by the representative consumer's willingness-to-pay for this change in utility. This is equal to the change in utility due to technology divided by the change in utility from wealth:

$$\frac{\pi[\tilde{u}_h^s d\Delta h - \tilde{u}_c^s dp]}{\pi\tilde{u}_c^s + (1-\pi)\tilde{u}_c^w}$$

We divide by the ex ante marginal utility of wealth rather than the marginal utility of consumption in the sick state because individuals have the ability to transfer wealth across states with indemnity insurance. In any case, under full and perfect indemnity insurance, (1) tells us the marginal utility of consumption is the same in each state so the value of treatment reduces to:

$$\pi\left[\frac{\tilde{u}_h^s}{\tilde{u}_c^s}d\Delta h - dp\right] \tag{2}$$

We call this term the "risk-free value of technology," (RFVT) because it represents what an individual would pay if he did not face any costly consumption risk from illness. It is worth noting that this calculation would be identical for a risk-neutral individual who finds it costless to bear risk.

RFVT is analogous to the standard formula for valuing health technology in the economics literature: the marginal value of health improvement,[5] multiplied by the gain in health, less the incremental price of the technology. However, there are two problems with the method the literature uses to value medical treatments. First, although RFVT provides theoretical motivation for the standard formula used in the literature, the standard formula is not strictly identical to RFVT. Second, even if the standard formula in the literature and the RFVT overlapped, the standard formula fails to capture important insurance value from medical technology. We explain the first problem in the remainder of this section. We explain the insurance value from medical innovation in the next section.

The literature varies in how it calculates the marginal value of health – a key input into the standard formula – and, in any case, does not use the marginal value of the health employed in the RFVT calculation. The RFVT calculation uses the consumer's willingness to pay for health assuming she has access to indemnity insurance: $\tilde{u}_h^s/\tilde{u}_c^s$. By contrast, the literature uses the marginal value of health when she does *not* have access to indemnity insurance. The reason is that people in real life do not have access to complete indemnity insurance markets. As a result, studies estimating the value of health, either through surveys or behavior, get an estimate of health from people for whom the marginal utility of wealth in the sick state is different from that in the well state, in contrast to (1).

Moreover, different studies employ different methods of valuing health, even among individuals without indemnity insurance. Some studies ask sick individuals how much they would be willing to pay (WTP) for certain health gains, i.e., $u_h^s/u_c^s$ (Pliskin, Shepard et al. 1980). Others ask healthy individuals how much they are willing to accept (WTA) to take on a risk, i.e., $u_h^w/u_c^w$ (Viscusi 1993). This differs from WTP not only in the marginal utility of wealth it employs, but also in the marginal utility of health it employs.[6] Finally, some studies employ a mix of measures – a meta-analysis of estimates from the literature. These may blur WTP and WTA measures depending on which studies are part of the sample.[7]

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[5] The ratio of marginal utility of health and consumption in (2) would be equal to the inverse of the marginal price of technology if health improvement was divisible and the individual were choosing the *optimal* level of health improvement to purchase. Because we are instead valuing an *incremental* increase in health improvement relative to no technology, the ratio is not equal to the inverse of marginal price.

[6] Many WTA estimates are drawn from labor market studies of the value of a statistical life (Viscusi 1993, Viscusi and Aldy 2003), which seek to estimate how much of a wage premium a worker would have to receive to take on a mortality risk. Such studies have a second problem which is that that the valuations are based on tradeoff between utility in an alive state and a dead state rather than between a well state and a sick (but alive) state. These studies convert mortality valuations into morbidity valuations using a lifetime consumption profile along with a theoretical construct like the quality-adjusted life-year (QALY) (Broom 1993).

[7] Typically, estimates of WTA are larger than estimates of WTP Boardman, A., D. Greenberg, A. Vining and D. Weimer (2010). Cost-Benefit Analysis. New York, Prentice-Hall., though that is an empirical result rather than an implication of utility theory. One case in which the two overlap is when utility is a function of the sum of consumption and health, i.e.,

The focus of this paper is not the gap between the marginal valuation of health employed in RFVT and in the economics literature. Rather, our focus is on identifying the risk-reduction value of health technology. Although neither WTP nor WTA from existing studies measure the marginal value of health in the sick state in the presence of full indemnity insurance, valuations that employ WTP estimates have a closer theoretical connection to RFVT because they focus on health in the sick rather than the well state. In the next section we show that even these valuations fail to capture the insurance value of technology.

## B: Insurance value of therapeutic technology

The second problem with the standard method employed in the literature to value medical treatment is that that it fails to value the role of technology in reducing costly consumption risk. Suppose that individuals cannot purchase indemnity insurance contracts, but can purchase only fee-for-service health insurance contracts. Under a fee-for-service contract, the individual can transfer money to the sick state, but only to pay for the price of medical care. The maximum transfer to the sick state is equal to $(1-\pi)\bar{p}$ and the maximum transfer from the healthy state is $\pi\bar{p}$, where $\bar{p} \leq p$, the price of the medical treatment.[8] When $\bar{p} = p$, the individual is said to have complete fee-for-service health insurance; when $\bar{p} < p$, the individual has incomplete insurance, e.g., deductibles, co-payments or annual caps. In this environment, the individual solves the problem:

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

To allow for incomplete health insurance, we separate the effects of a change in technology price $p$ and a change in health insurance availability $\bar{p}$. However, we allow the latter to depend on the former, i.e., we define the health insurance contract as $\bar{p}(p)$.

If the constraint fails to bind, the value of medical technology is equal to the risk free value of technology. In the non-trivial case where it binds, there is an additional "insurance value of technology," and we can write the individual's utility as:

$$\pi u(y^s - p + (1-\pi)\bar{p}(p), h^s + \Delta h) + (1-\pi)u(y^w - \pi\bar{p}(p), h^w)$$

The full value of a marginal improvement in medical technology is given by the willingness to pay for: the marginal change in health $(d\Delta h)$, plus the marginal change in insurance availability $(\bar{p}'(p)dp)$, minus the marginal change in the price $(dp)$. Denote by $\hat{u}_j^i$ the marginal utility of good $j$ in state $i$ in the economy without indemnity insurance. The change in utility associated with the marginal changes in these three parameters is given by:

$$(1-\pi)\pi[\hat{u}_c^s - \hat{u}_c^w]\bar{p}'(p)dp + \pi[\hat{u}_h^s d\Delta h - \hat{u}_c^s dp]$$

On the margin, the *ex ante* willingness-to-pay for a technology is equal to the expression above divided by the *ex ante* marginal utility of consumption. We use the *ex ante* marginal utility of consumption because health insurance is employed to pay for technology, and health insurance allows payment with wealth from both states. Because indemnity insurance markets are incomplete, we cannot use (1) to simplify the marginal utility

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$u(c+h)$. Then, the marginal valuation of health is always 1, regardless of indemnity insurance and whether one is valuing a health reduction or improvement.

[8] The sick consumer receives a transfer of $\bar{p}$ when sick, and must thus pay a premium of $q\bar{p}$ in each state. This results in a net transfer of $\bar{p} - q\bar{p} = (1-q)\bar{p}$ when sick.

of consumption to the marginal utility of consumption in the sick state, $\hat{u}_c^s$. However, the willingness-to-pay for technology can still be written as the sum of three components:

$$\pi \left\{ \overbrace{\left[\frac{\hat{u}_h^s}{\hat{u}_c^s} d\Delta h - dp\right]}^{\substack{Ex\ post\ consumer\ surplus \\ (standard\ formula)}} + \overbrace{\left(\frac{\hat{u}_h^s}{\hat{u}_c^s} d\Delta h - dp\right)\left[\frac{\hat{u}_c^s}{\pi \hat{u}_c^s + (1-\pi)\hat{u}_c^w} - 1\right]}^{Self-insurance\ value > 0} + \overbrace{(1-\pi)\frac{[\hat{u}_c^s - \hat{u}_c^w]}{\pi \hat{u}_c^s + (1-\pi)\hat{u}_c^w}\frac{d\bar{p}}{dp}dp}^{Market-insurability\ value > 0} \right\} \qquad (3)$$

The first term is the standard formula for calculating the value of treatment. It computes the ex post consumer surplus from treatment and is analogous to the "risk-free value" of therapeutic technology (RFVT), defined as before, except that the marginal value of health is the observed WTP for health.

The "self-insurance value" of therapeutic technology (SIVT) represents the additional value of a technology that accrues to an individual who is incompletely insured, holding the availability of fee-for-service health insurance (i.e., $\bar{p}$) fixed. Notice that it is proportional to ex post consumer surplus. In particular, the self-insurance value will be positive if the technology generates *ex post* consumer surplus *and* if the individual has positive demand for health insurance (i.e., if $\hat{u}_c^s > \pi\hat{u}_c^s + (1-\pi)\hat{u}_c^w$).

Finally, the "market-insurability value" of therapeutic technology (MIVT) represents the incremental value of being able to use health insurance to substitute for the indemnity insurance market. Medical technology is essential to this substitution because health insurance can only be used to fund consumption of medical care. Mathematically, market-insurability value is the willingness to pay for a marginal increase in $\bar{p}$, the constraint on the level of fee-for-service health insurance. This will be positive as long as the individual is incompletely insured (i.e., if $\hat{u}_c^s > \hat{u}_c^w$). Another way to put it is that market-insurability value is the value of reducing the gap in the marginal utility of consumption across states, holding fixed the level of health.

The appendix shows how these arguments can be generalized to inframarginal improvements in treatment. Our aim here is to show that standard estimates of the value of technology that employ the WTP to pay for health will tend to underestimate the value of technology because they ignore insurance value due to technology.

## II: THE VALUE OF PREVENTIVE TECHNOLOGY

Most medical technologies have some preventive dimension, and many are almost exclusively focused on prevention. For example, diabetes treatments are designed not only to improve the condition of a patient in diabetes, but also to prevent secondary complications like cardiovascular disease. At the other extreme, vaccines are administered to healthy patients and designed entirely to prevent illness rather than improve the current condition of the recipient. In this section we value technologies that prevent morbidity.

### A: The risk-free value of preventive technology

We consider a simple one-period model, similar to that of Ehrlich and Becker, in which the individual can both prevent and treat illness. Preventive technologies are paid for in both the sick and well states, but (absent financial insurance) treatment technologies are paid for in the sick state only. The preventive technology marginally reduces the probability of illness by $\Delta\pi$ at a price of $q$.[9] We focus on the case where there is a therapeutic technology to treat illness, because the presence of such technology is important to the risk-reduction value of preventive technology. As in the previous section, the therapeutic technology improves health by $\Delta h$ at a marginal price of $p$.

We begin once again by assuming the individual has access to indemnity insurance. Define the return on transfers of $x$ to the sick state as $\rho(x) = (1-x)/x$, where $\rho'(\mathrm{x}) < 0$. The fully insured individual's utility maximization problem can be written as:

$$\max_{\tau}(\pi-\Delta\pi)u(y^s-p-q+\rho(\pi-\Delta\pi)\tau, y^s+\Delta h)+(1-\pi+\Delta\pi)u(y^w-q-\tau,h^w)$$

The value created by the use of the preventive technology is:

$$\overbrace{\left\{\frac{(\tilde{u}^w-\tilde{u}^s)}{\tilde{u}_c^E}d\Delta\pi-dq\right\}}^{\substack{Consumer\ surplus \\ (standard\ formula)}}+\overbrace{\left\{(\pi-\Delta\pi)\frac{\tilde{u}_c^S}{\tilde{u}_c^E}(-\rho'(\pi-\Delta\pi))\tau(d\Delta\pi)\right\}}^{Terms\ of\ trade>0}$$

where $\tilde{u}_c^w$ and $\tilde{u}_c^s$ are the marginal utility of consumption in the well and sick states, respectively. We define $\tilde{u}_c^E=(\pi-\Delta\pi)u_c(y^s-p-q+\rho(\pi-\Delta\pi)\tau,h^s+\Delta h)+(1-\pi+\Delta\pi)u_c(y^w-q-\tau,h^w)$. This represents the expected marginal utility of consumption across states.

To the fully insured consumer, prevention has two components of value: the consumer surplus, equal to the value of the direct gain in utility less cost; and the risk-rating value that arises as a result of decreases in the price of transfers through indemnity insurance. The standard formula for valuing preventive technology only focuses on the consumer surplus and hence undervalues preventive technology even in the presence of indemnity insurance which insulates consumers from consumption risk. The second component is what Ehrlich & Becker (1972, pp. 646-47) call the terms of trade effects of self-protection.

## B: Insurance value of preventive technology

Now consider the case where there is no indemnity insurance market, but there is fee-for-service insurance that covers the purchase of the therapeutic medical technology. Fee-for-service health insurance does not cover the purchase of preventive technology. Because prevention must be purchased in both the sick and healthy states, fee-for-service health insurance does not cover its purchase. Health insurance is only valuable for purchasing treatment for sickness in period two.

In this type of economy, the consumer's expected utility maximization problem faces a constraint on resource transfer: $\tau \le (\pi-\Delta\pi)\bar{p}(p)$. Associate the Lagrange multiplier $\lambda$ with the resource transfer constraint. In this environment, the value created by the use of the preventive technology is:

$$\overbrace{\left\{\frac{(\hat{u}^w-\hat{u}^s)}{\hat{u}_c^E}(d\Delta\pi)-dq\right\}}^{\substack{Consumer\ surplus \\ (Standard\ formula)}}+\overbrace{\overbrace{\left\{(\pi-\Delta\pi)\frac{\hat{u}_c^S}{\hat{u}_c^E}(-\rho'(\pi-\Delta\pi))(d\Delta\pi)\right\}}^{Terms\ of\ trade>0}+\overbrace{\left\{-\frac{\lambda\bar{p}(p)}{\hat{u}_c^E}(d\Delta\pi)\right\}}^{Insurability\ cost<0}}^{Insurance\ value\ of\ self-protection>0}$$

The first two terms are similar to those in the fully indemnity insured case, except that we have replaced utility with full indemnity insurance with utility with health insurance. The last reflects the effect of

[9] To keep things simple, payment in our model is made in the same period as resolution of uncertainty, as Ehrlich & Becker (1972) and Rosen (1981).

prevention on the imperfect market for financial risk-transfer. The term is negative because prevention tightens the constraint ($\tau \leq (\pi - \Delta\pi)\bar{p}(p)$) on the amount of transfers to the sick state permitted by health insurance. From the first-order condition for transfers with health insurance, we know the sum of the risk-rating value and the insurability value is non-negative. The sum is positive only for risk-averse consumers, as was the insurance value of therapeutic technology. The appendix shows how these arguments can be generalized to inframarginal improvements in prevention.

Unlike in the case of therapeutic insurance, the consumer surplus value for preventive insurance differs for risk-averse individuals because imperfect insurance markets cause the term $\hat{u}_c^E$ to depend on the relative values of the marginal utility of consumption across sick and healthy states. The effect of an increase in risk is theoretically ambiguous. A reduction in the probability of being in the sick state can either increase or decrease the variability of the risk faced by the consumer. For example, reducing the probability from 0.6 to 0.5 increases variability while reducing it from 0.3 to 0.2 decreases variability.

We call the sum of the last two terms in the equation above the insurance value of self-protection (IVSP) because they are unique to risk-averse individuals. IVSP is not captured by the standard formula employed to value preventive technology. Moreover, IVSP has two non-obvious features. First, IVSP depends on the existence of therapeutic technology. In the absence of ex post therapy, the value of prevention is simply the standard formula. Preventing a disease with no effective treatments provides no insurance value, because the individual in this case is risk-neutral over changes in the probability of the sick and well states. The arrival of treatment technology, however, introduces *financial risk*, which is costly for risk-averse consumers to bear. Since it reduces the financial risk of paying for treatment, prevention provides more value to risk-averse consumers. Specifically, while the standard formula captures the costs saved when consumers avoid paying for therapy ex post, it ignores the incremental value of reducing financial risk. Second, health insurance actually lowers the terms-of-trade value from prevention because the transfers under health insurance coverage are keyed to the level of financial risk, which prevention reduces. That said, while fee-for-service health insurance may not have as much value – or contribute as much value to prevention – as indemnity insurance, it is better than no insurance.

# III: ESTIMATES OF VALUE OF MEDICAL INNOVATION AND HEALTH INSURANCE

This section provides empirical estimates of the self-insurance and market insurability values of therapeutic innovation using data obtained from the Cost-Effectiveness Analysis Registry (CEAR). We first provide an overview of cost-effectiveness analysis, which delivers the inputs needed for our calculations. We then describe our data and report estimation results.

## A: Overview of cost-effectiveness analysis

The cost-effectiveness of a medical intervention is the ratio of the intervention's cost to some measure of its benefit. One way to measure benefit is to employ Quality-Adjusted Life Years (QALYs). A QALY converts quality of life into years of good health. For example, if individuals are indifferent between living 9 months in perfect health and living 12 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 standardized metric for comparing health benefits across different treatments. Assigning a dollar value to QALYs allows researchers to compare health benefits to other consumer goods. [10]

[10] See Viscusi (1993) for a survey of the literature on estimating the statistical value of life.

For example, consider a one-year study of a new AIDS drug. Suppose this treatment significantly improves a patient's health status and thus increases her enjoyment of life. The patient's responses to a survey indicate that her quality of life was equal to $h^s = 0.7$ QALYs prior to treatment, but after treatment she enjoys $h^s + \Delta h = 0.9$ QALYs. The incremental value of the treatment is therefore equal to $\Delta h = 0.2$ QALYs. If the average individual values a QALY at $100,000 then the gross value of this drug to society is $20,000.

Of course, many studies cover a horizon of several years, not just one. In these cases researchers discount the future costs and benefits of a medical intervention according to the following formulas:

$$Cost = Price = \sum_{t=0}^{T-1} P_t(1 - r_c)^t \qquad Benefit = \sum_{t=0}^{T-1} \Delta h_t\left(1 - r_q\right)^t$$

The total cost of an intervention depends on the annual incremental cost, $P_t$, and is discounted at the rate $r_c$ over a time horizon of $T$ years. The total benefit is measured in annual incremental QALYs ($\Delta h_t$) and is discounted at the rate $r_q$.[11] The cost-effectiveness ratio is equal to $Cost/Benefit$.The advantages and disadvantages of using QALYs to measure health benefits are well known (Broome 1993, Bleichrodt and Quiggin 1999). For the purposes of this paper, the main advantage of the cost-effectiveness framework is that it provides a standardized metric that is used to estimate costs and benefits across a large number of different health studies. These real-world estimates correspond well to the parameters in our theoretical model and thus allow us to estimate accurately the relative importance of the self-insurance and market insurability values of therapeutic innovation in the economy.

## B: Data

CEAR is a collection of over 3,000 cost-effectiveness studies published between 1976 and 2012.[12] A study is included in the database if it (1) contains original research; (2) measures health benefits in QALYs; and (3) is published in English.

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 and discount rates. CEAR classifies each study into different intervention types. We define a therapeutic innovation to be any CEAR study classified "pharmaceutical", "surgical", "medical device", or "medical procedure". We define studies classified "immunization", "screening", or "health education nor behavior" as preventive innovations.[13]

We do not observe the time path of $\{P_t, \Delta h_t\}$ in the CEAR data. Instead, we assume that costs and benefits are evenly distributed over time, i.e., $P_t = P$ and $\Delta h_t = \Delta h$. These time-invariant values are easily derived from equations for $Cost$ and $Benefit$, which were shown earlier.

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.

CEAR also reports the utility weights for every health state considered in the cost-effectiveness studies. These utility weights range from 0 to 1 and are used to construct $h^s$, the quality of life in the pre-treatment (sick)

[11] The discount rates $r_c$ and $r_q$ are usually equal to each other. Only 8% of the studies in CEAR discount costs and benefits using different rates.

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

[13] The other categories, "care delivery", "diagnostic", "other", and "none/na", are excluded from our analysis.

state. For example, suppose there are two health states, A and B, with corresponding 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 $h^s = (w_a + w_b)/2$. Unfortunately, CEAR does not report what fraction of patients is in each health state for either the pre- or post-treatment groups. Instead, we assume that pre-treatment patients are uniformly distributed across health states.

CEAR assigns each treatment to one of seventy different disease categories. It does not, however, provide data on the probability of developing the disease. We address this by obtaining estimates of disease prevalence from the Medical Expenditure Panel Survey. The discharge rates are listed in Table 1 for the 15 most commonly studied diseases in CEAR. See the data appendix for details.

Our final therapeutic and preventive innovation samples consist of 1,188 and 425 observations, respectively. Summary statistics are provided in Table 2 and Table 3. Figure 1 displays the distribution of $\Delta h$ in our sample of therapeutic innovations. The majority of treatments produce small improvements in health ($\Delta h < 0.05$), but a few treatments produce large improvements, which skews the sample to the right. The largest health estimate, $\Delta h = 0.43$, corresponds to a cost-effectiveness study of imatinib mesilate (marketed as "Gleevec") for the treatment of advanced stage chronic myeloid leukemia (CML) (Gordois 2003). Prior to the introduction of Gleevec, CML was a highly fatal disease, but Gleevec allows clinically eligible patients to have a nearly normal life expectancy. Dialysis treatment for end-stage renal disease produces the second-largest estimate, $\Delta h = 0.33$.

Figure 2 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. There are three very expensive treatments: left ventricular assist devices for heart-failure patients and two different inhibitors for treatment of hemophilia top the list with prices of approximately $150,000. Although expensive, each of these three treatments generates large health improvements ($\Delta h \approx 0.15$). Not all expensive treatments are valuable: interferon beta-1b, a treatment for multiple sclerosis that helps prevent patients from becoming wheelchair-dependent, costs $22,000 but generates little health improvement ($\Delta h = 0.009$) (Forbes 1999).

Figure 3 displays the distribution of incremental health improvements for our preventive innovation sample. The distribution is again skewed to the right. The largest health improvement (QALY = 0.14) corresponds to a screening test for Hepatitis B. Early detection in asymptomatic individuals can prevent the disease from progressing to liver failure and hepatocellular carcinoma. (Ruggeri et al 2010 CITE).

Figure 4 shows that the distribution of treatment prices for our preventive innovation sample is also skewed to the right. The most expensive treatment is a protease inhibitor, which helps prevent *Mycobacterium avium* complex in HIV patients (Bayoumi 1998).

## C: Estimating the value of therapeutic innovation

We assume that consumers have Cobb-Douglas preferences 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 quality of an individual's health, $h$, can range from 0 to 1.

This specification cleanly separates risk-aversion from the elasticity of substitution between consumption and health. The former drives the total demand for insurance and risk-reduction, while the latter determines whether people wish to use insurance to transfer resources to or from the sick state. The sign of the effect of health on the marginal utility of consumption ($u_{ch}$) depends solely on $\sigma$. Health has a positive effect on the marginal utility of consumption if $\sigma < 1$ and a negative effect if $\sigma > 1$. If $\sigma = 1$ then the marginal utility of consumption is independent of health (state independence). All else equal, the value of insurance in the sick state is increasing in $\sigma$.

We set the parameters governing health and income in the healthy state, $h^w$ and $y^w$, equal to 1 and \$50,000, respectively. We use \$50,000 because this is approximately equal to the median income in the United States. The quality of health in the sick state, $h^s$, is obtained from CEAR. We assume that income in the sick state, $y^s$, is equal to $y^w$. This assumption is conservative because it minimizes the value of transferring wealth from the healthy state to the sick state. Employing an alternative, lower value for $y^s$ would increase our estimates of the self-insurance and market-insurance values of technology.

The price of the therapy, $p$, is equal to the annual price derived from the CEAR data. We set the incremental health benefit of the innovation, $\Delta h$, equal to the estimate of incremental QALYs obtained from CEAR.

We calibrate the parameters $\gamma$ and $\sigma$ using estimates from other studies of (1) the value of a life year; and (2) risk aversion. Estimates of the value of a life year range from \$100,000 to \$300,000 and correspond closely to what we call RFVT for a technology that increases life expectancy by one year. Because RFVT does not depend on $\sigma$, we use those estimates to calibrate $\gamma$.[14] Given our assumptions about income in the sick and healthy states, we set $\gamma = 0.3$.[15] At this value, an individual's *ex post* willingness to pay for a treatment that increases her health from 0.5 to 1 is \$81,000, which is approximately one-half the value of a life year.

The Arrow-Pratt measure of relative risk aversion over consumption in this model is equal to $R^c = 1 - \gamma(1 - \sigma) > 0$.[16] The proper value of risk aversion among real-world populations remains controversial. Chetty (2006) estimates a range of 0.15 to 1.78, but many studies have estimated much larger values.[17] We adopt $\sigma = 3$ as our preferred estimate, which corresponds to $R^c = 1.6$, but we also report results across a broad range of risk assumptions. As we shall see, the values of SIVT and MIVT relative to RFVT depend greatly on the assumed value of $\sigma$.

Because some of the treatments in CEAR result in large changes in health and are expensive, we employ the inframarginal analogue to our theoretical model in order to produce accurate estimates of RFVT, SIVT, and MIVT. See the appendix for a full derivation.

We report all estimates of RFVT, SIVT, and MIVT from an *ex ante* perspective by multiplying them by $\pi$, the probability of being in the sick state. Thus, our estimates should be regarded as the values accruing to an individual who is facing a risk of illness.

Before we turn to estimates from CEAR, we first illustrate how RFVT, SIVT, and MIVT change as a function of a technology's price. Figure 5 displays the results for the case where $h^s = 0.4$ and $\Delta h = 0.1$. When the price of treatment is low, most of the its value comes from RFVT and SIVT. As the price

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[14] The appendix, which includes a full derivation of this model, shows that only SIVT and MIVT depend on sigma.

[15] Employing different values of $\gamma$ affects the level of our estimates for RFVT, SIVT, and MIVT, but does not substantively affect their relative values, which is what we are primarily interested in.

[16] The formula for calculating relative risk aversion in a two-good model is derived by Dardanoni (1988).

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

increases, the value of transferring money across states becomes more important, as reflected by the increasing value of MIVT.[18] The total value of the treatment becomes negative as the price nears $30,000.

We now turn to our estimates from CEAR. Figure 6 shows that the distribution of RFVT in the 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 additional information to analysis of means. Figure 6 also shows that there are several technologies that generate negative RFVT, i.e., the *ex post* costs of these technologies exceeds the *ex post* benefits.

We report the mean and the 10th, 50th, and 90th percentile of our estimates in Table 4 for values of $\boldsymbol{\sigma}$ ranging from 0.5 to 8, which corresponds to a relative risk aversion range of 0.85 to 3.1. We weight our estimates by the prevalence of disease in order to produce an accurate estimate of the *ex ante* value of the treatments in the CEAR database. The mean value of RFVT, which is not a function of $\boldsymbol{\sigma}$, is $1,609. When $\boldsymbol{\sigma = 3}$, our preferred specification, the means of SIVT and MIVT are $1,768 and $41, respectively. The gains from SIVT and MIVT are increasing in $\boldsymbol{\sigma}$ because it 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 6).

When $\boldsymbol{\sigma}$ 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.[19] This is reflected in the negative values of MIVT in the first row of Table 4. When $\boldsymbol{\sigma}$ is greater than or equal to 1, MIVT will be positive for any treatment with a positive price.

Table 5 normalizes the SIVT and MIVT estimates in Table 4 by their corresponding RFVT values. When evaluated at the mean for $\sigma = 3$, it shows that each dollar of RFVT generates $1.10 in SIVT and $0.03 of MIVT. In other words, properly accounting for the total insurance benefits of therapeutic innovation increases its value by 113%.

Table 6 shows how our estimates vary by disease. The mean price of treatment for cardiovascular disease (CD) is $1,562 in CEAR. The mean RFVT, SIVT, and MIVT for CD are $568, $175, and $79, respectively. MIVT is generally small, although it is large for some categories, like "digestive diseases".

MIVT is small for many of the treatments in CEAR because most prices are relatively low. It is much larger when the price of treatment becomes a significant fraction of an individual's wealth. Table 7 shows how our estimates vary by price quantiles of treatment. RFVT does not always increase with price, indicating that costly treatments do not necessarily confer correspondingly large health benefits on the consumer. When evaluated at $\sigma = 3$ and at the 99th percentile of price ($26,121), MIVT is equal to $824, several orders of magnitude larger than its value when evaluated at the median price. Although expensive treatments may not generate much RFVT or SIVT, they always generate large MIVT. This agrees with the notion that insurance is more valuable for expensive items than for cheap items, regardless of whether those items generate consumer surplus.

Our estimates can also be employed to compare consumers' willingness to pay for the insurance value of technology and for the insurance value of health insurance. One complication is that, whereas SIVT is

[18] RFVT always decreases with price and MIVT always increases with price. Although in this example SIVT is decreasing with price, this is not a general result. SIVT depends on consumer surplus (which decreases in price) and the difference in marginal utilities across states, which increases in price. Thus, the overall effect of price on SIVT can be nonmonotonic because it depends on the relative values of consumer surplus and the difference in marginal utilities.

[19] See Finkelstein et al. (2013) for an empirical analysis and discussion of negative state dependence.

entirely due to technology, MIVT is attributable to both technology and health insurance: its value is equal to zero without one or the other. According to Table 5, however, even if MIVT is entirely credited to health insurance, technology creates about 40 times as much value as health insurance ($1.10 v. $0.03 of value) when evaluated at the mean. Table 7, however, shows that this is not true when price becomes large.

## D. Estimating the value of preventive innovation

We assume the same specification for $u(c,h)$ as in the case of therapeutic innovation. Because we are now analyzing preventive innovations, we attribute the incremental health benefit to a reduction in the probability of contracting the disease, $\Delta\pi$. Consumption of the preventive innovation decreases the probability of being in the sick state to $\pi^{\Delta} = \pi - \Delta\pi$.

Our theoretical analysis decomposed the value of preventive technology into three components: consumer surplus, terms of trade, and insurability cost. Estimating the latter two values requires the presence of therapeutic technology. Although CEAR provides data on both therapeutic and preventive technologies, we do not know how often or in what circumstances consumers utilize both simultaneously. Thus, we estimate the consumer surplus value of prevention (CSVP) only.

As discussed earlier, the effect of $\sigma$ on the value of CSVP is theoretically ambiguous. Estimating the effect of an increase in risk on CSVP is thus an empirical question. This is in contrast to therapeutic technology, where $\sigma$ has no effect on RFVT and a strictly positive effect on both SIVT and MIVT.

Figure 7 displays the distribution of the consumer surplus value of prevention (CSVP) in our sample when we set $\sigma = 3$. As with therapeutic technology, most treatments generate little value, although here the values are fairly symmetric about zero rather than skewed to the right.

Table 8 displays our estimates of CSVP for different values of $\sigma$. We find that an increase in $\sigma$ is associated with an increase in CSVP, indicating that risk-averse consumers value prevention more than risk-neutral consumers. Our preferred specification estimates that the mean CSVP is equal to $423.

# IV: CONCLUSION

When real-world health insurance markets are perfect, risk-averse consumers derive value from medical technologies that reduce the probability of bad events, limit the consequences of bad events, and expand the reach of financial health insurance. We refer to these as the self-protection, self-insurance, and market-insurance values of medical technology. All three components provide value to consumers above and beyond standard concepts of "ex post" consumer surplus.

These theoretical observations are empirically meaningful. New medical technologies treating disease provide substantial insurance value above and beyond standard consumer surplus. Under plausible assumptions, the insurance value substantially exceeds the consumer surplus value. Notably, "self-insurance" is often a much larger contributor of insurance value than "market insurance." The latter point suggests that medical technology alone does more to reduce health risk than financial 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.[20] Our results suggest that accounting for uncertainty would significantly increase their estimates.

[20] Murphy and Topel (2006) estimate the value of increases in both life expectancy and quality of life. They find that the latter "may be the more valuable dimension of recent health advances" (p. 902).

The ability of medical innovation to function as an insurance device influences not just the level of value, but also its distribution in the population. More risk-averse groups benefit disproportionately from new medical technologies, holding clinical benefit and utilization fixed. At fairly typical, middle-of-the-road estimates of risk-aversion, the risk-management value of new technology is about as large as the traditional consumer surplus. However, among highly risk-averse groups, the risk-management value could be significantly larger than surplus. From a distributional perspective, previous work by McClellan and Skinner (2006) suggests that poorer groups derive more value from insurance than richer groups. In this context, medical technology might be more redistributive than previously believed.

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. From a dynamic perspective, 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. US 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.

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# APPENDIX

## A: The value of inframarginal improvements from therapeutic medical technology

The exposition in the text characterized value for marginal improvements in technology and marginal prices. It is straightforward to formalize expressions for inframarginal improvements based on this machinery as well. Suppose one wants to value a technology that improves health in the sick state by a discrete amount $\Delta$ and has a discrete price of $p$. Define $p(x)$ as a pricing function that maps an incremental health gain $x$ into a price. For example, if the pricing function is linear, then $p(x) = px/\Delta$. An implicit assumption is that, in a competitive market for example, the cost of a technology is a function of health improvement. Similarly, define the function $\pi^*(\mathrm{x})$, as the optimal indemnity transfer as a function of the health improvement, accounting for the mapping of health improvement onto price.

Assuming that health insurance constraint binds, the inframarginal analogue to the ex post consumer surplus is given by:

$$RFVT \equiv \int_0^{\Delta} \frac{u_h(y^s - p + (1-\pi)\bar{p}(p(x)), h^s + x)}{u_c(y^s - p + (1-\pi)\bar{p}(p(x)), h^s + x)} dx - p$$

The inframarginal self-insurance value is given by:

$$SIVT \equiv \int_0^{\Delta} \left[\frac{\hat{u}_h^s}{\hat{u}_c^s} - p'(x)\right] \left[\frac{\hat{u}_c^s}{\pi\hat{u}_c^s + (1-\pi)\hat{u}_c^w} - 1\right] dx$$

The arguments inside $\hat{u}_h^s$ and $\hat{u}_c^s$ are the same as in the expression for CS. Moreover, $\hat{u}_c^w \equiv u_c(y^w - \pi\bar{p}\big(p(x)\big), h^w)$. Finally, the inframarginal market-insurability value is:

$$MIVT \equiv (1-\pi) \int_0^{\Delta} \frac{[\hat{u}_c^s - \hat{u}_c^w]}{\pi\hat{u}_c^s + (1-\pi)\hat{u}_c^w} \bar{p}'(p(x))p'(x)dx$$

Once again, the arguments inside $u_c^w$, $u_h^s$, and $u_c^s$ are as above.

Our empirical section makes two assumptions that simplify these expressions. First we assume that consumer utility takes the form

$$u(c,h) = ((c^{\gamma}h^{1-\gamma})^{1-\sigma} - 1)/(1-\sigma) \; if \; \sigma \neq 1$$

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

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. Second, we assume the consumer has access to fee-for-service insurance ($\bar{p} = p$) and that the pricing function is linear, which implies that $p(x) = px/\Delta$. Plugging these assumptions in yields

$$RFVT = \frac{1-\gamma}{\gamma} \int_0^{\Delta} \frac{c^s}{h^s + x} dx - p$$

where $c^s = y^s - p + (1-\pi)px/\Delta$.

The inframarginal self-insurance value is

$$SIVT = \int_0^{\Delta} \left[\frac{1-\gamma}{\gamma}\frac{c^s}{h^s+x} - \frac{p}{\Delta}\right]\left[\frac{1}{\pi + (1-\pi)\left(\frac{c^w}{c^s}\right)^{\gamma(1-\sigma)-1}\left(\frac{h^w}{h^s+x}\right)^{(1-\gamma)(1-\sigma)}} - 1\right]dx$$

where $c^w = y^w - \pi p x/\Delta$.

The inframarginal market-insurance value is

$$MIVT = (1-\pi)\gamma\frac{p}{\Delta}\int_0^{\Delta}\left[\frac{1-\left(\frac{c^w}{c^s}\right)^{\gamma(1-\sigma)-1}\left(\frac{h^w}{h^s+x}\right)^{(1-\gamma)(1-\sigma)}}{\pi + (1-\pi)\left(\frac{c^w}{c^s}\right)^{\gamma(1-\sigma)-1}\left(\frac{h^w}{h^s+x}\right)^{(1-\gamma)(1-\sigma)}}\right]dx$$

We have state independence if $\sigma = 1$, in which case SIVT and MIVT can be simplified:

$$SIVT = \int_0^{\Delta}\left[\frac{1-\gamma}{\gamma}\frac{c^s}{h^s+x} - \frac{p}{\Delta}\right]\left[\frac{1}{\pi + (1-\pi)\frac{c^s}{c^w}} - 1\right]dx$$

$$MIVT = (1-\pi)\gamma\frac{p}{\Delta}\int_0^{\Delta}\left[\frac{c^w - c^s}{\pi c^w + (1-\pi)c^s}\right]dx$$

## B: The value of inframarginal improvements in preventive medical technology

As before, we can extend this analysis to compute inframarginal improvements in prevention. Define $\pi$ as the initial probability of illness, and define $\Delta\pi$ as the change in this probability. Finally, define the price of prevention as the function $q(x)$, where $x$ is the change in probability of sickness.

For a given treatment technology, the inframarginal analogue to the consumer surplus value of prevention is then given by:

$$RFVP \equiv \int_0^{\Delta\pi}\left[\frac{u(y^w-\tau, h^w) - u(c^s - p + \rho(x)\tau, h^s + \Delta h)}{(\pi - x)u_c(c^s - p + \rho(x)\tau, h^s + \Delta h) + (1-\pi+x)u_c(y^w - \tau, h^w)} - q'(x)\right]dx$$

The inframarginal terms of trade value of prevention is:

$$TOTVP \equiv \int_0^{\Delta\pi} x\left[\frac{u(y^s - p + \rho(x)\tau, h^s + \Delta h)}{u_c(c - q(x), h)}\right]\left(-\rho'(x)\right)\tau dx$$

Finally, the inframarginal insurability cost of prevention:

$$ICP \equiv \int_0^{\Delta\pi} -\frac{\lambda(x)\bar{p}(p)}{u_c(c-q(x),h)}dx$$

Our empirical analysis makes the same functional form assumptions as our therapeutic analysis but we only estimate CSVP. Plugging in those assumptions yields

$$CSVP = \frac{1}{\gamma(1-\sigma)}\int_0^{\Delta\pi}\frac{\left(\frac{c^w}{c^s}\right)^{\gamma(1-\sigma)}\left(\frac{h^w}{h^s}\right)^{(1-\gamma)(1-\sigma)} - 1}{(\pi - x)(c^s)^{-1} + (1-\pi+x)\left(\frac{c^w}{c^s}\right)^{\gamma(1-\sigma)}(c^w)^{-1}\left(\frac{h^w}{h^s}\right)^{(1-\gamma)(1-\sigma)}}dx - q$$

where $c^w = y^w - qx/\Delta\pi$ and $c^s = y^s - qx/\Delta\pi$. If $\sigma = 1$ this expression simplifies to

$$RFVP = \frac{1}{\gamma}\int_0^{\Delta\pi} \frac{\ln((c^w)^\gamma (h^w)^{1-\gamma}) - \ln((c^s)^\gamma (h^s)^{1-\gamma})}{(\pi - x)(c^s)^{-1} + (1-\pi+x)(c^w)^{-1}} dx - q$$

## C. 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 codes.[21] For example, tuberculosis corresponds to the ICD-9 codes 10 through 18.

Some CEAR disease classifications were calculated as residuals. For example, the CEAR database classifications included three types of respiratory diseases: "COPD", "Asthma", and "Other Respiratory". These are all subcategories of "Diseases of the Respiratory System" (ICD-9 codes 460-519). We calculated the discharge count for the "Other Respiratory" classification by subtracting the counts of "COPD" (codes 490-492 and 496) and "Asthma" (code 493) from the total count of "Diseases of the Respiratory System" in the NHDS. Appendix Table 9 shows the results of our mapping.

We then calculated the prevalence of each disease category using the 1996 – 2011 Medical Expenditure Panel Surveys (MEPS). Each MEPS survey includes a file that records the ICD-9 code corresponding to every condition suffered by a respondent. We mapped these codes into the disease categories given by Table Appendix Table 9 and calculated disease prevalence by year. Our final estimate corresponds to the average across the 1996 – 2011 survey years.

[21] See ftp.cdc.gov/pub/Health_Statistics/NCHS/Publications/ICD9-CM/2008

## TABLES AND FIGURES

**Table 1. Estimated probabilities, by disease.**

| Disease name | Probability x 100 | Number of CEAR observations |
|---|---|---|
| Musculoskeletal and Rheumatologic Diseases | 22.869 | 110 |
| Infectious | 19.568 | 107 |
| Cardiovascular Diseases | 19.126 | 82 |
| Breast Cancer | 0.486 | 71 |
| Ischaemic Heart Disease | 2.263 | 54 |
| Malignant Neoplasms | 3.380 | 53 |
| Non-Ischaemic Heart Disease - Other | 4.213 | 52 |
| HIV/AIDS | 0.077 | 49 |
| Vision | 8.267 | 45 |
| Diabetes Mellitus | 5.505 | 39 |
| Digestive Diseases | 14.404 | 37 |
| Other Musculoskeletal | 0.298 | 35 |
| Endocrine Disorders | 17.863 | 32 |
| Hematologic Cancers | 0.230 | 31 |
| Cerebrovascular Disease | 1.126 | 27 |

Notes: The second column lists the estimates we employ for the probability of being in the sick state for the 15 most common diseases in CEAR. Source: 1996-2011 MEPS surveys.

**Table 2. CEAR summary statistics for sample of therapeutic innovations.**

| | Mean | SD | Min | Max |
|---|---|---|---|---|
| Horizon (years) | 54.387 | 35.945 | 1 | 85 |
| QALY discount rate | 0.033 | 0.009 | 0.015 | 0.06 |
| Cost discount rate | 0.036 | 0.009 | 0.015 | 0.06 |
| Q (QALYs) | 0.034 | 0.049 | 0.0000 | 0.4287 |
| P (2011 dollars) | $2,173.85 | $8,597.13 | $0.07 | $162,583.00 |
| Probability of disease x 100 | 8.44 | 8.78 | 0.035 | 38.27 |

Notes: Sample consists of 1,188 interventions.

**Table 3. CEAR summary statistics for sample of preventive innovations.**

| | Mean | SD | Min | Max |
|---|---|---|---|---|
| Horizon (years) | 66.711 | 29.497 | 1 | 100 |
| QALY discount rate | 0.031 | 0.005 | 0.015 | 0.05 |
| Cost discount rate | 0.032 | 0.005 | 0.03 | 0.05 |
| Q (QALYs) | 0.008 | 0.019 | 0.0000 | 0.1465 |
| P (2011 dollars) | $239.19 | $848.44 | $0.01 | $10,793.30 |
| Probability of disease x 100 | 11.196 | 9.508 | 0.042 | 38.267 |

Notes: Sample consists of 1,188 interventions.

**Table 4. Estimates of RFVT, SIVT, and MIVT for different values of sigma.**

| | RFVT | | | | SIVT | | | | MIVT | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Sigma | P10 | Median | P90 | Mean | P10 | Median | P90 | Mean | P10 | Median | P90 | Mean |
| 0.5 | -14.27 | 171.85 | 2,358.65 | 1,609.42 | -233.61 | -9.60 | 0.22 | -330.16 | -11.90 | -0.85 | -0.03 | -0.66 |
| 1 | -14.27 | 171.85 | 2,358.65 | 1,609.42 | -0.08 | 0.24 | 34.02 | -2.75 | 0.00 | 0.04 | 4.03 | 6.10 |
| 3 | -14.27 | 171.85 | 2,358.65 | 1,609.42 | -5.62 | 43.66 | 1,343.95 | 1,768.02 | 0.21 | 5.29 | 89.89 | 40.59 |
| 5 | -14.27 | 171.85 | 2,358.65 | 1,609.42 | -12.51 | 100.13 | 3,025.77 | 2,664.43 | 0.45 | 11.36 | 197.40 | 83.09 |
| 8 | -14.27 | 171.85 | 2,358.65 | 1,609.42 | -26.73 | 204.30 | 5,552.81 | 3,598.17 | 0.88 | 21.63 | 352.95 | 150.05 |

Notes: Sample is 1,188 interventions from CEAR. Estimates are weighted by the prevalence of disease. Units are 2011 dollars.

**Table 5. Normalized estimates of SIVT, and MIVT for different values of risk aversion (sigma).**

| | P10 | | Median | | P90 | | Mean | |
|---|---|---|---|---|---|---|---|---|
| Sigma | SIVT | MIVT | SIVT | MIVT | SIVT | MIVT | SIVT | MIVT |
| 0.5 | 16.37 | 0.83 | -0.06 | 0.00 | 0.00 | 0.00 | -0.21 | 0.00 |
| 1 | 0.01 | 0.00 | 0.00 | 0.00 | 0.01 | 0.00 | 0.00 | 0.00 |
| 3 | 0.39 | -0.01 | 0.25 | 0.03 | 0.57 | 0.04 | 1.10 | 0.03 |
| 5 | 0.88 | -0.03 | 0.58 | 0.07 | 1.28 | 0.08 | 1.66 | 0.05 |
| 8 | 1.87 | -0.06 | 1.19 | 0.13 | 2.35 | 0.15 | 2.24 | 0.09 |

Notes: Sample is 1,188 interventions from CEAR. Estimates are weighted by the prevalence of disease and are normalized by the corresponding RFVT value.

**Table 6. Estimates of RFVT, SIVT, and MIVT by disease (sigma=3).**

| Disease name | Number of CEAR observations | Mean Price | Mean RFVT | Mean SIVT | Mean MIVT |
|---|---|---|---|---|---|
| Musculoskeletal and Rheumatologic Diseases | 110 | $1,819.45 | $686.70 | $461.45 | $88.94 |
| Infectious | 107 | $803.36 | $814.83 | $440.49 | $23.21 |
| Cardiovascular Diseases | 82 | $1,562.38 | $568.19 | $174.95 | $79.08 |
| Breast Cancer | 71 | $785.84 | $19.19 | $13.33 | $0.85 |
| Ischaemic Heart Disease | 54 | $751.65 | $29.04 | $24.28 | $3.45 |
| Malignant Neoplams | 53 | $2,194.81 | $90.88 | $234.41 | $24.05 |
| Non-Ischaemic Heart Disease - Other | 52 | $3,705.50 | $136.35 | -$144.12 | $96.98 |
| HIV/AIDS | 49 | $736.97 | $3.75 | $1.53 | $0.06 |
| Vision | 45 | $3,086.70 | $501.42 | $680.59 | $81.07 |
| Diabetes Mellitus | 39 | $400.75 | $54.86 | $24.32 | $3.49 |
| Digestive Diseases | 37 | $2,716.51 | $650.54 | $1,689.03 | $105.29 |
| Other Musculoskeletal | 35 | $1,090.31 | $0.98 | $1.83 | $0.92 |
| Endocrine Disorders | 32 | $1,165.69 | $1,166.41 | $272.07 | $28.73 |
| Hematologic Cancers (Lymphomas, Leukaemia) | 31 | $4,499.98 | $14.95 | $10.77 | $4.05 |
| Cerebrovascular Disease | 27 | $643.44 | $67.75 | $66.54 | $1.76 |

Notes: This table lists the mean price of treatment for the 15 most common diseases in CEAR, along with estimated mean values of RFVT, SIVT, and MIVT. Units are 2011 dollars.

**Table 7. Estimates of RFVT, SIVT, and MIVT by price quantiles of treatment.**

| | RFVT | | | | SIVT | | | | MIVT | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Sigma** | **P10** | **P50** | **P90** | **P99** | **P10** | **P50** | **P90** | **P99** | **P10** | **P50** | **P90** | **P99** |
| 0.5 | 1.79 | 9.55 | 354.15 | -4,002.80 | -0.10 | -0.47 | 3.57 | -1,041.67 | 0.00 | -0.03 | 0.51 | 351.30 |
| 1 | 1.79 | 9.55 | 354.15 | -4,002.80 | 0.00 | 0.04 | 14.53 | -1,302.06 | 0.00 | 0.00 | 2.07 | 439.14 |
| 3 | 1.79 | 9.55 | 354.15 | -4,002.80 | 0.49 | 2.36 | 62.43 | -2,442.71 | 0.01 | 0.14 | 8.91 | 823.78 |
| 5 | 1.79 | 9.55 | 354.15 | -4,002.80 | 1.11 | 5.25 | 117.56 | -3,704.25 | 0.03 | 0.31 | 16.77 | 1,249.14 |
| 8 | 1.79 | 9.55 | 354.15 | -4,002.80 | 2.36 | 10.93 | 216.02 | -5,668.47 | 0.07 | 0.66 | 30.80 | 1,912.00 |

Notes: Sample is 1,188 interventions from CEAR. P10 corresponds to price of $23.74, P50 to $392.25, P90 to $4,024.95, and P99 to $26,120.79. Units are 2011 dollars.

**Table 8. Estimates of CSVP for different values of sigma.**

| | CSVP | | | |
|---|---|---|---|---|
| **Sigma** | **P10** | **Median** | **P90** | **Mean** |
| 0.5 | -169.55 | -0.43 | 271.88 | 98.00 |
| 1 | -169.15 | -0.42 | 286.61 | 153.58 |
| 3 | -167.57 | 0.90 | 347.00 | 423.34 |
| 5 | -157.93 | 2.28 | 407.17 | 774.83 |
| 8 | -135.31 | 4.50 | 433.53 | 1,416.73 |

Notes: Sample is 425 interventions from CEAR. Estimates are weighted by the prevalence of disease. Units are 2011 dollars

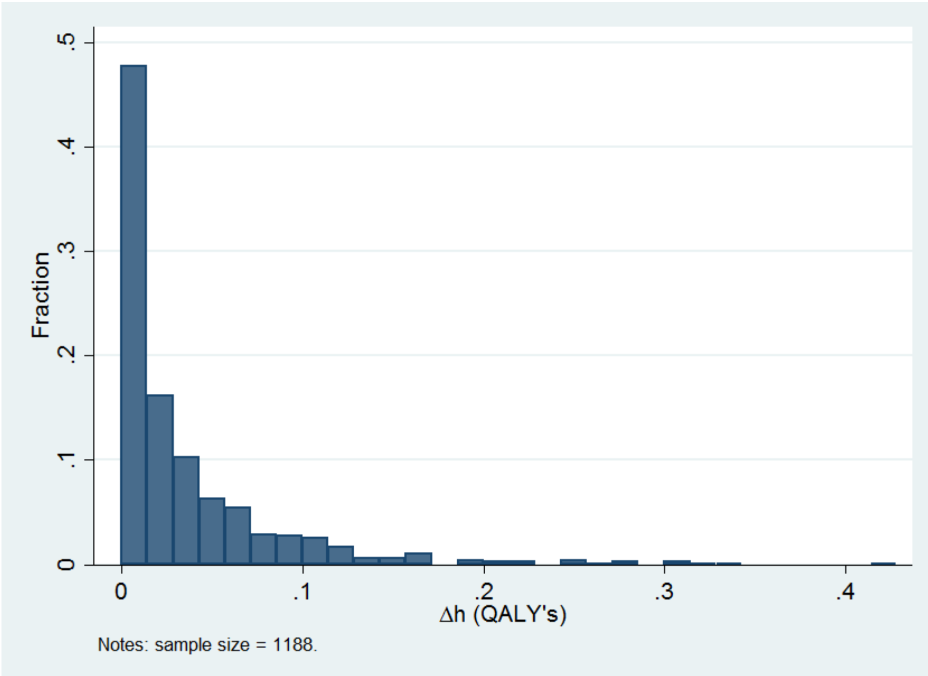


**Figure 1. This figure displays the distribution of $\Delta h$, a measure of health improvement that ranges from 0 to 1, in our therapeutic innovation sample.**

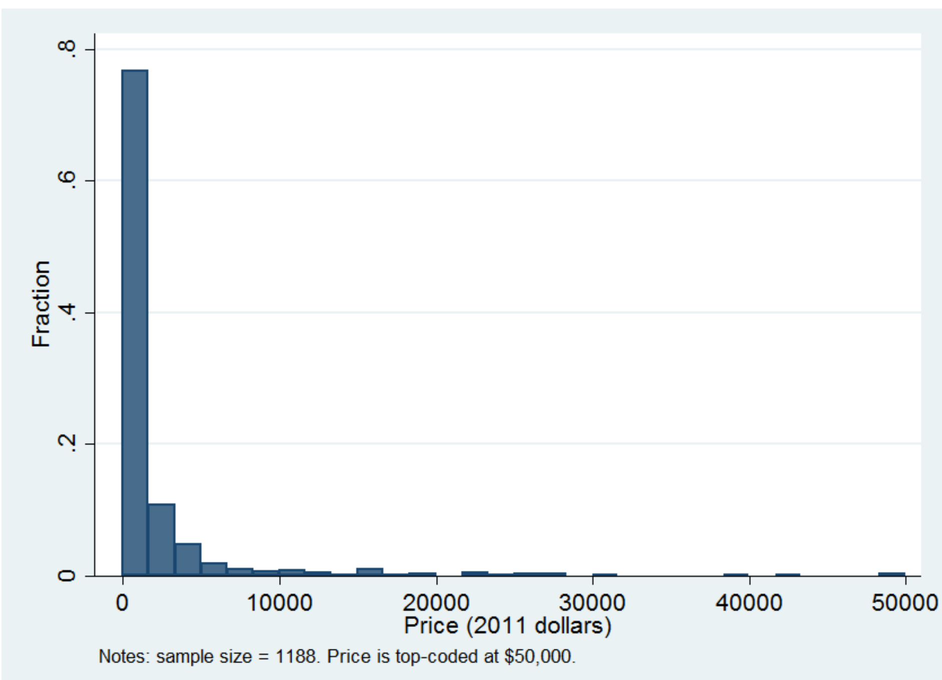


**Figure 2. This figure displays the distribution of prices for the treatments in our therapeutic innovation sample. Price is top-coded at $50,000 to make the data easier to display.**

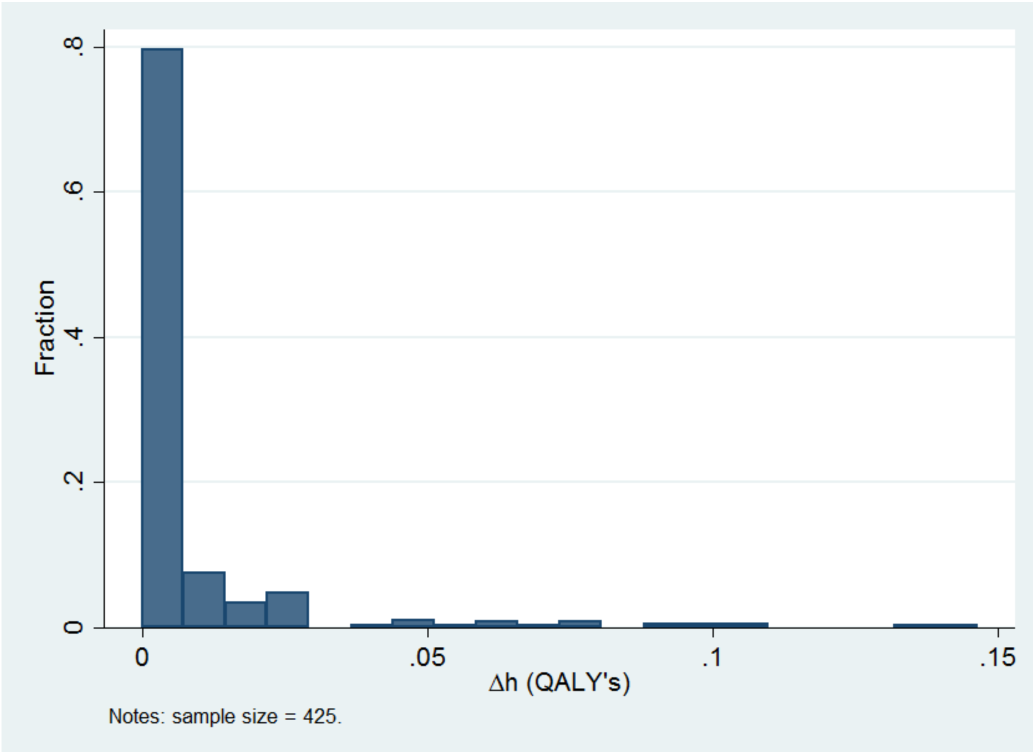


**Figure 3. This figure displays the distribution of $\Delta h$, a measure of health improvement that ranges from 0 to 1, in our preventive innovation sample.**

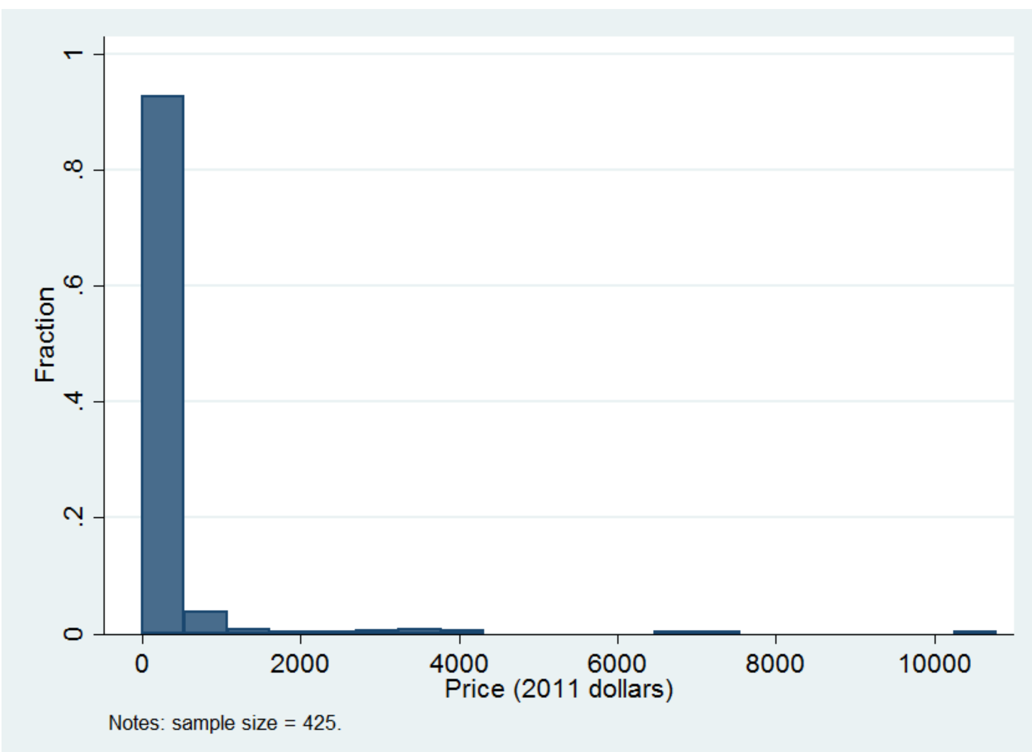


**Figure 4. This figure displays the distribution of prices for the treatments in our preventive innovation sample.**

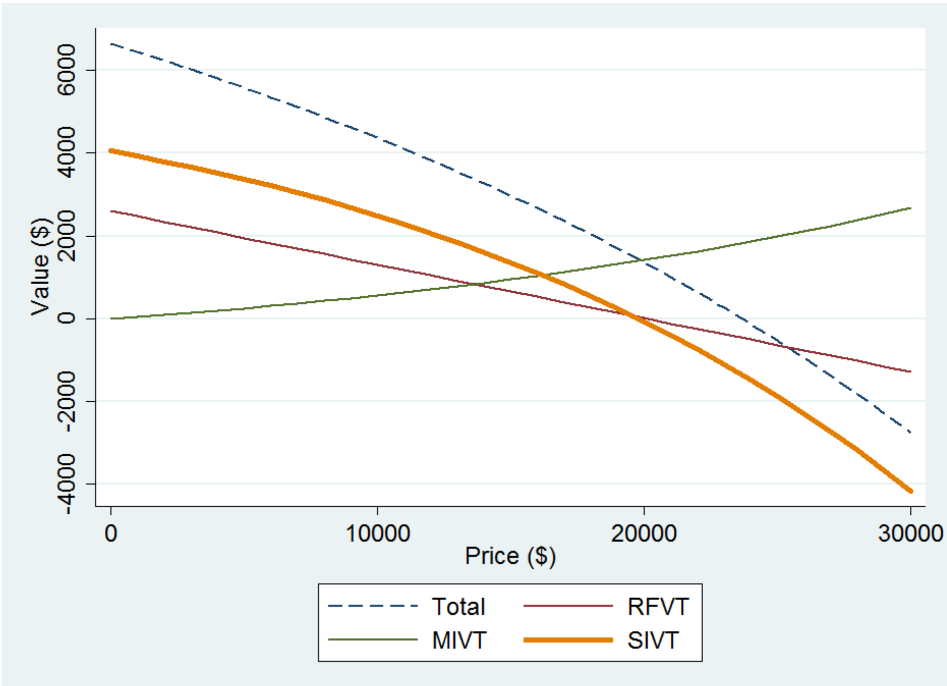


**Figure 5. Simulated estimates of RFVT, SIVT, and MIVT as a function of price. Total = RFVT + SIVT + MIVT. Parameters are $\gamma = 0.3$, $\sigma = 3$, $y^w = y^s$ =$50,000, $h^w$= 1, $h^s$= 0.4, and $\Delta h$ = 0.1.**

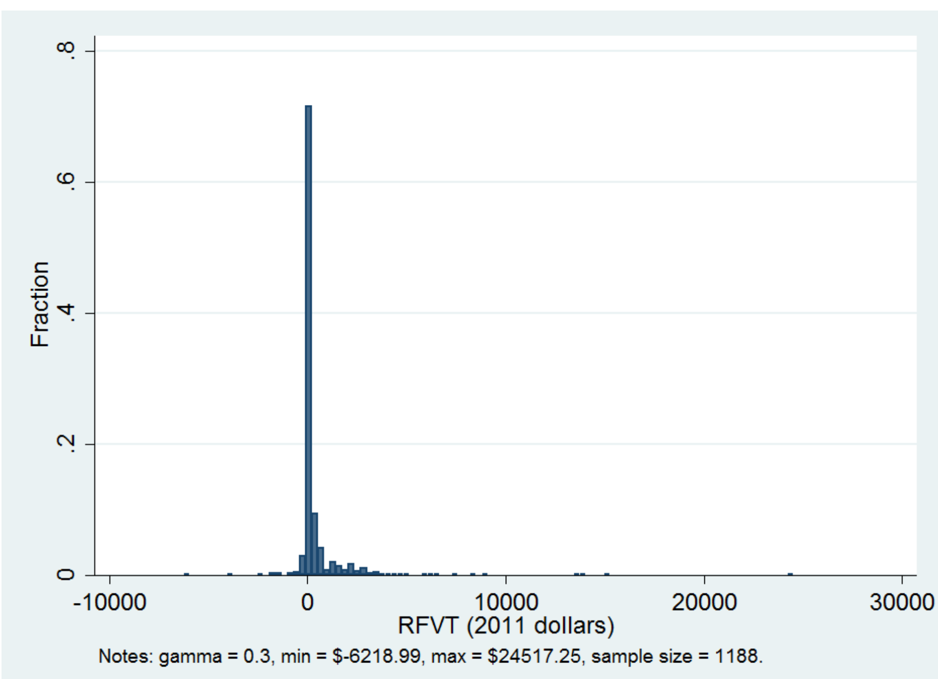


**Figure 6. Distribution of the risk-free value of treatment (RFVT) in CEAR therapeutic innovation sample.**

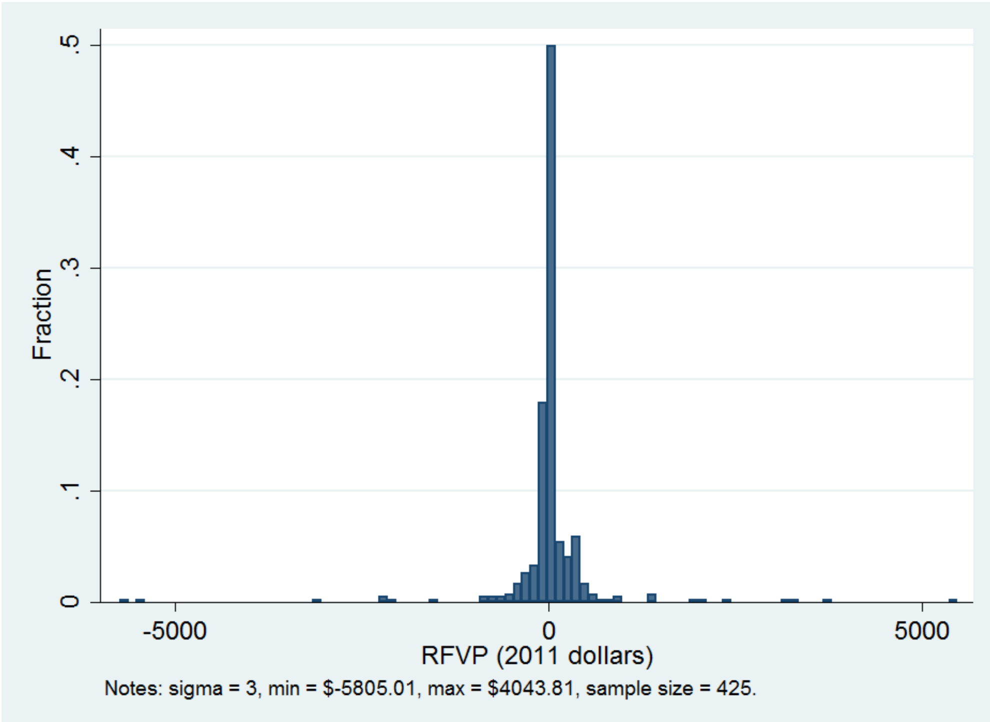


**Figure 7. Distribution of consumer-surplus value of prevention (CSVP) in CEAR preventive innovation sample.**

# APPENDIX TABLES

**Table 9. Estimated prevalences for the thirty most common CEAR disease classifications.**

| CEAR disease classification | ICD-9-CM codes | Estimated prevalence x 100 |
|---|---|---|
| Musculoskeletal and Rheumatologic Diseases | 710-739 | 22.87 |
| Infectious | 0-139 | 19.57 |
| Cardiovascular Diseases | 390-459 | 19.13 |
| Ischaemic Heart Disease | 410-414 | 2.26 |
| Malignant Neoplams | 140-208, 230-234, 209.31-209.36, 209.7 | 3.38 |
| Breast Cancer | 174-175, 198.81, 233 | 0.49 |
| Diabetes Mellitus | 250 | 5.51 |
| HIV/AIDS | 42 | 0.08 |
| Digestive Diseases | 520-579 | 14.40 |
| Neuro-Psychiatric and Neurological Conditions | 290-359 | 17.50 |
| Cerebrovascular Disease | 430-438 | 1.13 |
| Hematology - Other | 286-289 | 0.35 |
| Non-Ischaemic Heart Disease - Other | 391, 392.0, 393-398, 402, 404, 415, 416, 420-429 | 4.21 |
| Hypertension | 401 | 15.13 |
| Endocrine Disorders | 240-259, 270-279 | 17.86 |
| Genito-Urinary Diseases | 580-629 | 10.36 |
| Vision | 360-379 | 8.27 |
| Rheumatoid Arthritis | 714 | 0.85 |
| Depression and Bipolar Affective Disorder | 296 | 0.73 |
| Kidney Disease | 580-589 | 0.24 |
| Other Neoplasms | 210-229 | 1.67 |
| Maternal and Child Health (Perinatal) | 630-679, 760-779 | 0.80 |
| Injuries/Exposures | 800-999 | 17.62 |
| Lung Cancer | 162, 176.4, 197.0, 197.3, 231.1, 231.2 | 0.15 |
| Skin Diseases (Non-Cancer) | 680-709 | 9.07 |
| Substance Abuse Disorders | 291, 292, 303, 304, 305.0, 305.2-305.9 | 0.38 |
| Hematologic Cancers (Lymphomas, Leukaemia) | 196, 200-208 | 0.23 |
| Alzheimer's and Other Dementias | 290, 294, 331.0 | 0.44 |
| Respiratory Diseases | 460-519 | 38.27 |
| Colorectal Cancer | 153, 154, 197.5, 230.3-230.6 | 0.18 |

Source: Medical Expenditure Panel Survey, 1996-2011