ONLINE APPENDIX: Not For Publication

A No Trade Condition

This section provides a more formal exposition of the no trade condition in Section 2. Consider a policy that provides a small payment, db, in the event of being unemployed and is financed with a small payment in the event of being employed, $d\tau$, offered to those with observable characteristics X. Moreover, assume for simplicity that

By the envelope theorem, the utility impact of buying such a policy will be given by

$$dU = -\left(1 - p\left(\theta\right)\right) v'\left(c_e\left(\theta\right)\right) d\tau + p\left(\theta\right) u'\left(c_u\left(\theta\right)\right) db$$

which will be positive if and only if

$$\frac{p\left(\theta\right) u'\left(c_u\left(\theta\right)\right)}{\left(1 - p\left(\theta\right)\right) v'\left(c_e\left(\theta\right)\right)} \geq \frac{d\tau}{db} \tag{14}$$

The LHS of equation (14) is a type θ's willingness to pay (i.e. marginal rate of substitution) to move resources from the event of being employed to the event of being unemployed.[61] The RHS of equation (14), $\frac{d\tau}{db}$, is the cost per dollar of benefits of the insurance policy.

Let $\bar{\Theta}\left(\frac{d\tau}{db}\right)$ denote the set of all individuals, θ, who prefer to purchase the additional insurance at price $\frac{d\tau}{db}$ (i.e. those satisfying equation (14)). An insurer's profit from a type θ is given by $\left(1 - p\left(\theta\right)\right)\tau - p\left(\theta\right) b$. Hence, the insurer's marginal profit from trying to sell a policy with price $\frac{d\tau}{db}$ is given by

$$d\Pi = \underbrace{E\left[1 - p\left(\theta\right) | \theta \in \bar{\Theta}\left(\frac{d\tau}{db}\right)\right] d\tau}_{\text{Premiums Collected}} - \underbrace{E\left[p\left(\theta\right) | \theta \in \bar{\Theta}\left(\frac{d\tau}{db}\right)\right] db}_{\text{Benefits Paid}} - \underbrace{\left(dE\left[p\left(\theta\right) | \theta \in \bar{\Theta}\left(\frac{d\tau}{db}\right)\right]\right)\left(\tau + b\right)}_{\text{Moral Hazard}}$$

The first term is the amount of premiums collected, the second term is the benefits paid out, and the third term is the impact of additional insurance on its cost. If more insurance increases the probability of unemployment, $dE\left[p\left(\theta\right)\right] > 0$, then it reduces premiums collected, τ, and increases benefits paid, b.[62]

However, for the first dollar of insurance when $\tau = b = 0$, the moral hazard cost to the insurer is zero. This insight, initially noted by Shavell (1979), suggests moral hazard does not affect whether insurers' first dollar of insurance is profitable – a result akin to the logic that deadweight loss varies with the square of the tax rate.

The first dollar of insurance will be profitable if and only if

$$\frac{d\tau}{db} \geq \frac{E\left[p\left(\theta\right) | \theta \in \bar{\Theta}\left(\frac{d\tau}{db}\right)\right]}{E\left[1 - p\left(\theta\right) | \theta \in \bar{\Theta}\left(\frac{d\tau}{db}\right)\right]} \tag{15}$$

If inequality (15) does not hold for any possible price, $\frac{d\tau}{db}$, then providing private insurance will not be profitable at any price. The market will unravel a la Akerlof (1970). Under the natural assumption[63] that profits are concave in b and τ, the inability to profitably sell a small amount of insurance also rules out the inability to sell larger insurance contracts.

To this point, the model allows for an arbitrary dimensionality of unobserved heterogeneity, θ. To provide a clearer expression of how demand relates to underlying fundamentals, such as marginal rates of substitution and beliefs, it is helpful to impose a dimensionality reduction on the unobserved heterogeneity.

Assumption A1. *(Uni-dimensional Heterogeneity) Assume the mapping $\theta \to p\left(\theta\right)$ is 1-1 and continuously differentiable in b and τ in an open ball around $b = \tau = 0$. Moreover, the marginal rate of substitution, $\frac{p}{1-p}\frac{u'\left(c_u\left(p\right)\right)}{v'\left(c_e\left(p\right)\right)}$, is increasing in p.*

Assumption A1 states that the underlying heterogeneity can be summarized by ones' belief, $p\left(\theta\right)$. In this case, the adverse selection will take a particular threshold form: the set of people who would be attracted to a contract for which type $p\left(\theta\right)$ is indifferent will be the set of higher risks whose probabilities exceed $p\left(\theta\right)$. Let P denote the random variable corresponding to the distribution of probabilities chosen in the population in the status quo world

[61] Note that, because of the envelope theorem, the individual's valuation of this small insurance policy is independent of any behavioral response. While these behavioral responses may impose externalities on the insurer or government, they do not affect the individuals' willingness to pay.

[62] To incorporate observable characteristics, one should think of the expectations as drawing from the distribution of θ conditional on a particular observable characteristic, X.

[63] See Appendix A.3 for a micro-foundation of this assumption.

without a private unemployment insurance market, $b=\tau=0$.[64] And, let $c_u(p)$ and $c_e(p)$ denote the consumption of types $p(\theta)$ in the unemployed and employed states of the world. Under Assumption A1, equation (15) can be re-written as:

$$\frac{u'(c_u(p))}{v'(c_e(p))} \leq T(p) \quad \forall p \tag{16}$$

where $T(p)$ is given by

$$T(p) = \frac{E[P|P \geq p]}{E[1-P|P \geq p]}\frac{1-p}{p}$$

which is the pooled cost of worse risks, termed the "pooled price ratio" in Hendren (2013). The market can exist only if there exists someone who is willing to pay the markup imposed by the presence of higher risk types adversely selecting her contract. Here, $\frac{u'(c_u(p))}{v'(c_e(p))}-1$ is the markup individual p would be willing to pay and $T(p)-1$ is the markup that would be imposed by the presence of risks $P \geq p$ adversely selecting the contract. This suggests the pooled price ratio, $T(p)$, is the fundamental empirical magnitude desired for understanding the frictions imposed by private information.

The remainder of this Appendix further discusses the generality of the no trade condition. A.1 discusses multi-dimensional heterogeneity. Appendix A.3 illustrates that while in principle the no trade condition does not rule out non-marginal insurance contracts (i.e. b and $\tau>0$), in general a monopolist firm's profits will be concave in the size of the contract; hence the no trade condition also rules out larger contracts. Appendix A.2 also discusses the ability of the firm to potentially offer menus of insurance contracts instead of a single contract to screen workers.

A.1 Multi-Dimensional Heterogeneity

This section solves for the no-trade condition when there does not exist a one-to-one mapping between θ and $p(\theta)$. In this case, there is potentially heterogeneous willingness to pay for additional UI for different types θ with the same $p(\theta)$. I assume for simplicity that the distribution of $p(\theta)$ has full support on $[0,1]$ and the distribution of $\frac{u'(c_e(\theta))}{v'(c_u(\theta))}$ has full support on $[0,\infty)$ (this is not essential, but significantly shortens the proof). I show that there exists a mapping, $f(p): A \rightarrow \Theta$, where $A \subset [0,1]$ such that the no trade condition reduces to testing

$$\frac{u'(c_u(f(p)))}{u'(c_e(f(p)))} \leq T(p) \quad \forall p$$

To see this, fix a particular policy, $\frac{d\tau}{db}$, and consider the set of θ that are willing to pay for this policy:

$$E\left[p(\theta)|\theta \in \bar{\Theta}\left(\frac{d\tau}{db}\right)\right]$$

Without loss of generality, there exists a function $\tilde{p}\left(\frac{d\tau}{db}\right)$ such that

$$E\left[p(\theta)|\theta \in \bar{\Theta}\left(\frac{d\tau}{db}\right)\right] = E\left[p(\theta)|p(\theta) \geq \tilde{p}\left(\frac{d\tau}{db}\right)\right]$$

so that the average probability of the types selecting $\frac{d\tau}{db}$ is equal to the average cost of all types above $\tilde{p}\left(\frac{d\tau}{db}\right)$. Without loss of generality, one can assume that $\tilde{p}$ is strictly increasing in $\frac{d\tau}{db}$ so that $\tilde{p}^{-1}$ exists.[65]

I construct $f(p): A \rightarrow \Theta$ as follows. Define A to be the range of $\tilde{p}$ when taking values of $\frac{d\tau}{db}$ ranging from 0 to ∞. For each p, define $f(p)$ to be a value(s) of θ such that the willingness to pay equals $\tilde{p}^{-1}(p)$:

$$\frac{p}{1-p}\frac{u'(c_e(f(p)))}{v'(c_u(f(p)))} = \tilde{p}^{-1}(p)$$

Now, suppose $\tilde{p}^{-1}(p) \leq T(p)$ for all p. One needs to establish that inequality (15) does not hold for any $\frac{d\tau}{db}$:

$$\frac{d\tau}{db} \leq \frac{E\left[p(\theta)|\theta \in \bar{\Theta}\left(\frac{d\tau}{db}\right)\right]}{E\left[1-p(\theta)|\theta \in \bar{\Theta}\left(\frac{d\tau}{db}\right)\right]}$$

[64] In other words, the random variable P is simply the random variable generated by the choices of probabilities, $p(\theta)$, in the population.

[65] If $\tilde{p}$ is not strictly increasing (e.g. because of "advantageous selection"), it will be strictly more profitable to an insurance company to sell the insurance at a higher price. Hence, one need not test the no trade condition for such intermediate values of $\frac{d\tau}{db}$ where $\tilde{p}$ is decreasing in p.

To see this, note that

$$\frac{E\left[p(\theta)\,|\theta \in \bar{\Theta}\left(\frac{d\tau}{db}\right)\right]}{E\left[1-p(\theta)\,|\theta \in \bar{\Theta}\left(\frac{d\tau}{db}\right)\right]} = \frac{E\left[p(\theta)\,|p(\theta) \geq \tilde{p}\left(\frac{d\tau}{db}\right)\right]}{1-E\left[p(\theta)\,|p(\theta) \geq \tilde{p}\left(\frac{d\tau}{db}\right)\right]}$$

so that we wish to show that

$$\frac{E\left[p(\theta)\,|p(\theta) \geq \tilde{p}\left(\frac{d\tau}{db}\right)\right]}{1-E\left[p(\theta)\,|p(\theta) \geq \tilde{p}\left(\frac{d\tau}{db}\right)\right]} \geq \frac{d\tau}{db} \tag{17}$$

for all $\frac{d\tau}{db}$. Note that the set A is generated by the variation in $\frac{d\tau}{db}$, so that testing equation (17) is equivalent to testing this equation for all $p$in the range of A:

$$\frac{E\left[p(\theta)\,|p(\theta) \geq p\right]}{1-E\left[p(\theta)\,|p(\theta) \geq p\right]} \geq \tilde{p}^{-1}(p) \quad \forall p \in A$$

which is equivalent to

$$\frac{E\left[p(\theta)\,|p(\theta) \geq p\right]}{1-E\left[p(\theta)\,|p(\theta) \geq p\right]} \geq \frac{p}{1-p}\frac{u'\left(c_e\left(f(p)\right)\right)}{v'\left(c_u\left(f(p)\right)\right)} \quad \forall p \in A$$

which proves the desired result.

Intuitively, it is sufficient to check the no trade condition for the set of equivalent classes of types with the same willingness to pay for $\frac{d\tau}{dp}$. Within this class, there exists a type that one can use to check the simple uni-dimensional no trade condition.

A.2 Robustness to Menus

Here, I illustrate how to nest the model into the setting of Hendren (2013), then apply the no trade condition in Hendren (2013) to rule out menus in this more complex setting with moral hazard. I assume here that there are no additional choices, a, other than the choice p, although the presence of such additional choices should not alter the proof as long as they are not observable to the insurer. With this simplification, the only distinction relative to Hendren (2013) is the introduction of the moral hazard problem in choosing p. This section shows that allowing p to be a choice doesn't make trade any easier than in a world where $p(\theta)$ is exogenous and not affected by the insurer's contracts; hence the no trade condition results from Hendren (2013) can be applied to rule out menus.

I consider the maximization program of a monopolist insurer offering a menu of insurance contracts. Whether there exists any implementable allocations other than the endowment corresponds to whether there exists any allocations other than the endowment which maximize the profit, π, subject to the incentive and participation constraints.

Without loss of generality, the insurer can offer a menu of contracts to screen types, $\{\nu(\theta), \Delta(\theta)\}_{\theta\in\Gamma}$ where $\nu(\theta)$ specifies a total utility provided to type θ, $v(\theta) = p(\theta)\,u(c_u(\theta)) + (1-p(\theta))\,v(c_e(\theta)) - \Psi(p;\theta)$, and $\Delta(\theta)$ denotes the difference in utilities if the agent becomes unemployed, $\Delta(\theta) = u(c_u(\theta)) - v(c_e(\theta))$. Note that $\nu(\theta)$ implicitly contains the disutility of effort.

Given the menu of contracts offered by the insurer, individuals choose their likelihood of unemployment. Let $\hat{q}(\Delta, \theta)$ denote the choice of probability of employment for a type θ given the utility difference between employment and unemployment, Δ, so that the agent's effort cost is $\Psi(\hat{q}(\Delta;\theta)\,\theta)$. Note that a type θ that accepts a contract containing Δ will choose a probability of employment $\hat{q}(\Delta;\theta)$ that maximizes their utility. I assume that $\hat{q}$ is weakly increasing in Δ for all θ.

Let $C_u(x) = u^{-1}(x)$ and $C_e(x) = v^{-1}(x)$ denote the consumption levels required in the employed and unemployed state to provide utility level x. Let $\pi(\Delta, \nu; \theta)$ denote the profits obtained from providing type θ with contract terms ν and Δ, given by

$$\pi(\Delta, \nu; \theta) = \hat{q}(\Delta;\theta)\left(c_e^e - C_e\left(v - \Psi(\Delta;\theta)\right)\right) + \left(1-\hat{q}(\Delta;\theta)\right)\left(c_u^e - C_u\left(\nu - \Delta - \Psi(\Delta;\theta)\right)\right)$$

Note that the profit function takes into account how the agents' choice of p varies with Δ.

Throughout, I maintain the assumption that profits of the monopolist are concave in (ν, Δ). Such concavity can be established in the general case when u is concave and individuals do not choose p (see Hendren (2013)). But, allowing individuals to make choices, p, introduces potential non-convexities into the analysis. However, it is natural to assume that if a large insurance contract would be profitable, then so would a small insurance contract. In Section A.3 below, I show that global concavity of the firm's profit function follows from reasonable assumptions on the individuals' utility function. Intuitively, what ensures global concavity is to rule out a case where small amounts of insurance generate large increases in marginal utilities (and hence increase the demand for insurance).

I prove the sufficiency of the no trade condition for ruling out trade by mapping it into the setting of Hendren (2013). To do so, define $\tilde{\pi}(\nu, \Delta; \theta)$ to be the profits incurred by the firm in the alternative world in which individuals choose p as if they faced their endowment (i.e. face no moral hazard problem). Now, in this alternative world, individuals still obtain total utility ν by construction, but must be compensated for their lost utility from effort because they can't re-optimize. But, note this compensation is second-order by the envelope theorem. Therefore, the marginal profitability for sufficiently small insurance contracts is given by

$$\pi\left(\nu,\Delta;\theta\right)\leq\tilde{\pi}\left(\nu,\Delta;\theta\right)$$

Now, define the aggregate profits to an insurer that offers menu $\{\nu\left(\theta\right),\Delta\left(\theta\right)\}_{\theta}$ by

$$\Pi\left(\nu\left(\theta\right),\Delta\left(\theta\right)\right)=\int\pi\left(\nu\left(\theta\right),\Delta\left(\theta\right);\theta\right)d\mu\left(\theta\right)$$

and in the world in which p is not affected by Π,

$$\tilde{\Pi}\left(\nu\left(\theta\right),\Delta\left(\theta\right)\right)=\int\pi\left(\nu\left(\theta\right),\Delta\left(\theta\right);\theta\right)d\mu\left(\theta\right)$$

So, for small variations in ν and Δ, we have that

$$\Pi\left(\nu\left(\theta\right),\Delta\left(\theta\right)\right)\leq\tilde{\Pi}\left(\nu\left(\theta\right),\Delta\left(\theta\right)\right)$$

because insurance causes an increase in p. Now, Hendren (2013) shows that the no trade condition implies that $\tilde{\Pi}\leq0$ for all menus, $\{\nu\left(\theta\right),\Delta\left(\theta\right)\}$. Therefore, the no trade condition also implies $\Pi\leq0$ for local variations in the menu $\{\nu\left(\theta\right),\Delta\left(\theta\right)\}$ around the endowment. Combining with the concavity assumption, this also rules out larger deviations.

Conversely, if the no trade condition does not hold, note that the behavioral response is continuous in Δ, so that sufficiently small values of insurance allow for a profitable insurance contract to be traded.

A.3 Concavity Assumption and Sufficient Conditions for Concavity

The presence of moral hazard in this multi-dimensional screening problem induces the potential for non-convexities in the constraint set. Such non convexities could potentially limit the ability of local variational analysis to characterize the set of implementable allocations. To be specific, let $\pi\left(\Delta,\mu;\theta\right)$ denote the profit obtained from type θ if she is provided with total utility μ and difference in utilities Δ,

$$\pi\left(\Delta,\mu;\theta\right)=\left(1-\hat{p}\left(\Delta;\theta\right)\right)\left(c_e^e-C_v\left(\mu-\Psi\left(1-\hat{p}\left(\Delta;\theta\right)\right)\right)\right)+\hat{p}\left(\Delta;\theta\right)\left(c_u^e-C_u\left(\mu-\Delta-\Psi\left(1-\hat{p}\left(\Delta;\theta\right)\right)\right)\right)$$

To guarantee the validity of our variational analysis for characterizing when the endowment is the only implementable allocation, it will be sufficient to require that $\pi\left(\Delta,\mu;\theta\right)$ is concave in $\left(\Delta,\mu\right)$.

Assumption. *$\pi\left(\Delta,\mu;\theta\right)$ is concave in $\left(\Delta,\mu\right)$ for each θ*

This assumption requires the marginal profitability of insurance to decline in the amount of insurance provided. If the agents choice of p is given exogenously (i.e. does not vary with Δ), then concavity of the utility functions, u and v, imply concavity of $\pi\left(\Delta,\mu;\theta\right)$. Assumption A.3 ensures that this extends to the case when p is a choice and can respond to θ.

Claim. If $\Psi'''\left(q;\theta\right)>0$ for all θ and $\frac{u'\left(c_u^e\right)}{v'\left(c_e^e\right)}\leq2$ then π is globally concave in $\left(\mu,\Delta\right)$.

For simplicity, we consider a fixed θ and drop reference to it. Profits are given by

$$\pi\left(\Delta,\mu\right)=\hat{q}\left(\Delta\right)\left(c_e^e-C_e\left(\mu-\Psi\left(\hat{q}\left(\Delta\right)\right)\right)\right)+\left(1-\hat{q}\left(\Delta\right)\right)\left(c_u^e-C_u\left(\mu-\Delta-\Psi\left(\hat{q}\left(\Delta\right)\right)\right)\right)$$

The goal is to show the Hessian of π is negative semi-definite. I proceed in three steps. First, I derive conditions which guarantee $\frac{\partial^2\pi}{\partial\Delta^2}<0$. Second, I show that, in general, we have $\frac{\partial^2\pi}{\partial\mu^2}<0$. Finally, I show the conditions provided to guarantee $\frac{\partial^2\pi}{\partial\Delta^2}<0$ also imply the determinant of the Hessian is positive, so that both eigenvalues of the Hessian must be negative and thus the matrix is negative semi-definite.

A.3.1 Conditions that imply $\frac{\partial^2\pi}{\partial\Delta^2}<0$

Taking the first derivative with respect to Δ, we have

$$\begin{aligned}\frac{\partial\pi}{\partial\Delta} &= \frac{\partial\hat{q}}{\partial\Delta}\left(c_e^e-c_u^e+C_u\left(\mu-\Delta-\Psi\left(\hat{q}\left(\Delta\right)\right)\right)\right)\\ &\quad-\left(1-\hat{q}\left(\Delta\right)\right)C_u'\left(\mu-\Delta-\Psi\left(\hat{q}\left(\Delta\right)\right)\right)-\hat{q}\left(\Delta\right)C_e'\left(\mu-\Psi\left(\hat{q}\left(\Delta\right)\right)\right)\end{aligned}$$

Taking another derivative with respect to Δ, applying the identity $\Delta = \Psi'(\hat{p}(\Delta))$, and collecting terms yields

$$\begin{aligned}\frac{\partial^2 \pi}{\partial \Delta^2} = & -\Big[(1-\hat{q}(\Delta))(1+\Delta)^2 C_u''(\mu-\Delta-\Psi(\hat{q}(\Delta))) + \hat{q}(\Delta)\left(\Delta \hat{q}'(\Delta)\right)^2 C''(\mu-\Psi(\hat{q}(\Delta)))\Big] \\ & + \frac{\partial \hat{q}}{\partial \Delta}\left[(1-\hat{q}(\Delta))C'(\mu-\Delta-\Psi(\hat{q}(\Delta))) + \hat{q}(\Delta)C'(u-\Psi(\hat{q}(\Delta))) - \left(2+2\Delta\hat{q}'(\Delta)\right)C'(\mu-\Delta-\Psi(\hat{q}(\Delta)))\right] \\ & + \frac{\partial^2 \hat{q}}{\partial \Delta^2}\left[c_e^e - c_u^e + C(\mu-\Delta-\Psi(\hat{q}(\Delta))) - C(\mu-\Psi(\hat{q}(\Delta))) + (1-\hat{q}(\Delta))\Delta C'(\mu-\Delta-\Psi(\hat{q}(\Delta))) + \hat{q}(\Delta)C'(\mu-\Psi(\hat{q}(\Delta\right.\end{aligned}$$

We consider these three terms in turn. The first term is always negative because $C'' > 0$. The second term, multiplying $\frac{\partial \hat{q}}{\partial \Delta}$, can be shown to be positive if

$$(1+\hat{q}(\Delta))C'(\mu-\Delta-\Psi(\hat{q}(\Delta))) \geq \hat{q}(\Delta)C'(\mu-\Delta)$$

which is necessarily true whenever

$$\frac{u'(c_u^e)}{v'(c_e^e)} \leq 2$$

This inequality holds as long as people are willing to pay less than a 100% markup for a small amount of insurance, evaluated at their endowment.

Finally, the third term is positive as long as $\Psi''' > 0$. To see this, one can easily verify that the term multiplying $\frac{\partial^2 \hat{q}}{\partial \Delta^2}$ is necessarily positive. Also, note that $\frac{\partial^2 \hat{q}}{\partial \Delta^2} = \frac{-\Psi'''}{(\Psi'')^2}$. Therefore, if we assume that $\Psi''' > 0$, the entire last term will necessarily be negative. In sum, it is sufficient to assume $\frac{u'(c_u^e)}{v'(c_e^e)} \leq 2$ and $\Psi''' > 0$ to guarantee that $\frac{\partial^2 \pi}{\partial \Delta^2} < 0$.

A.3.2 Conditions that imply $\frac{\partial^2 \pi}{\partial \mu^2} < 0$

Fortunately, profits are easily seen to be concave in μ. We have

$$\frac{\partial \pi}{\partial \mu} = -(1-\hat{q}(\Delta))C'(\mu-\Delta-\Psi(\hat{q}(\Delta))) - \hat{q}(\Delta)C'(\mu-\Psi(\hat{q}(\Delta)))$$

so that

$$\frac{\partial^2 \pi}{\partial \mu^2} = -(1-\hat{q}(\Delta))C''(\mu-\Delta-\Psi(\hat{q}(\Delta))) - \hat{q}(\Delta)C''(\mu-\Psi(\hat{q}(\Delta)))$$

which is negative because $C'' > 0$.

A.3.3 Conditions to imply $\frac{\partial^2 \pi}{\partial \Delta^2}\frac{\partial^2 \pi}{\partial \mu^2} - \left(\frac{\partial^2 \pi}{\partial \Delta \partial \mu}\right) > 0$

Finally, we need to ensure that the determinant of the Hessian is positive. To do so, first note that

$$\frac{\partial^2 \pi}{\partial \mu \partial \Delta} = (1-\hat{q}(\Delta))C''(\mu-\Delta-\Psi(\hat{q}(\Delta)))\left(1+\Delta\hat{q}'(\Delta)\right) + \hat{q}(\Delta)C''(\mu-\Psi(\hat{q}(\Delta)))\Delta\hat{q}'(\Delta)$$

Also, we note that under the assumptions $\Psi''' > 0$ and $\frac{u'(c_u^e)}{v'(c_e^e)} \leq 2$, we have the inequality

$$\frac{\partial^2 \pi}{\partial \Delta^2} < -\Big[(1-\hat{q}(\Delta))(1+\Delta)^2 C_u''(\mu-\Delta-\Psi(\hat{q}(\Delta))) + \hat{q}(\Delta)\left(\Delta\hat{q}'(\Delta)\right)^2 C''(\mu-\Psi(\hat{q}(\Delta)))\Big]$$

Therefore, we can ignore the longer terms in the expression for $\frac{\partial^2 \pi}{\partial \Delta^2}$ above. We multiply the RHS of the above equation with the value of $\frac{\partial^2 \pi}{\partial \mu^2}$ and subtract $\left(\frac{\partial^2 \pi}{\partial \Delta \partial \mu}\right)^2$. Fortunately, many of the terms cancel out, leaving the inequality

$$\begin{aligned}\frac{\partial^2 \pi}{\partial \Delta^2}\frac{\partial^2 \pi}{\partial \mu^2} - \left(\frac{\partial^2 \pi}{\partial \Delta \partial \mu}\right)^2 \geq \; & (1-\hat{q}(\Delta))\hat{q}(\Delta)\left(1+\Delta\hat{q}'(\Delta)\right)^2 C''(\mu-\Delta-\Psi(\hat{q}(\Delta)))C''(\mu-\Psi(\hat{q}(\Delta))) \\ & + \hat{q}(\Delta)(1-\hat{q}(\Delta))\left(\Delta\hat{q}'(\Delta)\right)^2 C''(\mu-\Psi(\hat{q}(\Delta)))C''(\mu-\Delta-\Psi(\hat{q}(\Delta))) \\ & - 2(1-\hat{q}(\Delta))\hat{q}(\Delta)\left(1+\Delta\hat{q}'(\Delta)\right)\Delta\hat{q}'(\Delta)C''(\mu-\Delta-\Psi(\hat{q}(\Delta)))C''(\mu-\Psi(\hat{q}(\Delta)))\end{aligned}$$

which reduces to the inequality

$$\frac{\partial^2 \pi}{\partial \Delta^2}\frac{\partial^2 \pi}{\partial \mu^2} - \left(\frac{\partial^2 \pi}{\partial \Delta \partial \mu}\right)^2 \geq \hat{q}(\Delta)(1-\hat{q}(\Delta))C''(\mu-\Delta-\Psi(\hat{q}(\Delta)))C''(\mu-\Psi(\hat{q}(\Delta)))K(\mu,\Delta)$$

where

$$\begin{aligned} K(\mu,\Delta) &= \left(1+\Delta\hat{q}'(\Delta)\right)^2+\left(\Delta\hat{q}'(\Delta)\right)^2-2\Delta\hat{q}'(\Delta)-2\left(\Delta\hat{q}'(\Delta)\right)^2 \\ &= 1 \end{aligned}$$

So, since $C''>0$, we have that the determinant must be positive. In particular, we have

$$\frac{\partial^2\pi}{\partial\Delta^2}\frac{\partial^2\pi}{\partial\mu^2}-\left(\frac{\partial^2\pi}{\partial\Delta\partial\mu}\right)^2 \geq \hat{q}(\Delta)(1-\hat{q}(\Delta))C''(\mu-\Delta-\Psi(\hat{q}(\Delta)))C''(\mu-\Psi(\hat{q}(\Delta)))$$

A.3.4 Summary

As long as $\Psi'''>0$ and $\frac{u'\left(c_u^e\right)}{v'\left(c_e^e\right)}\leq 2$, the profit function is globally concave. Empirically, I find that $\frac{u'\left(c_u^e\right)}{v'\left(c_e^e\right)}\leq 2$. Therefore, the unsubstantiated assumption for the model is that the convexity of the effort function increases in p, $\Psi'''>0$. An alternative statement of this assumption is that $\frac{\partial^2\hat{q}}{\partial\Delta^2}<0$, so that the marginal impact of Δ on the employment probability is declining in the size of Δ. Put differently, it is an assumption that providing utility incentives to work has diminishing returns.

Future work can derive the necessary conditions when individuals can make additional actions, $a(\theta)$, in response to unemployment. I suspect the proofs can be extended to such cases, but identifying the necessary conditions for global concavity would be an interesting direction for future work.

A.4 Motivating the Average Pooled Price Ratio when Insurers don't know P

To see the theoretical relevance of $E[T(P)]$, suppose an insurer seeks to start an insurance market by randomly drawing an individual from the population and, perhaps through some market research, learns exactly how much this individual is willing to pay. The insurer offers a contract that collects \$1 in the event of being employed and pays an amount in the unemployed state that makes the individual perfectly indifferent to the policy. If p is the probability this individual will become unemployed, then all risks $P\geq p$ will choose to purchase the policy as well. The profit per dollar of revenue will be

$$r(p)=\frac{u'(c_u(p))}{v'(c_e(p))}-T(p)$$

So, if the original individual was selected at random from the population, the expected profit per dollar would be positive if and only if

$$E\left[\frac{u'(c_u(p))}{v'(c_e(p))}\right]\geq E[T(P)]$$

If the insurer is randomly choosing contracts to try to sell, the average pooled price ratio, $E[T(P)]$, provides information on whether or not a UI market would be profitable.

B Details of Empirical Approach

B.1 Proof of Proposition 1

I prove the proposition in two steps. First, I show that $cov\left(P,\frac{m(P)}{P}\right)\leq 0$. Then, I use this result to prove the Proposition.

Lemma 1. For any P, it must be the case that $cov\left(P,\frac{m(P)}{P}\right)\leq 0$.

Proof: note that

$$m(P)=E[P-p|P\geq p]$$

so that

$$cov\left(P,\frac{m(P)}{P}\right)=E[m(P)]-E[P]E\left[\frac{m(P)}{P}\right]$$

So, we wish to show that

$$\frac{E[m(P)]}{E[P]}<E\left[\frac{m(P)}{P}\right]$$

Note that:

$$E\left[\frac{m(P)}{P}\right]=E\left[\frac{\frac{1}{1-F(P)}\int(\tilde{p}-P)f(\tilde{p})d\tilde{p}}{P}\right]=E\left[\frac{E[\tilde{p}|\tilde{p}\geq P]}{P}\right]-1=E_PE_{\tilde{p}}\left[\frac{\tilde{p}}{P}|\frac{\tilde{p}}{P}\geq 1\right]-1$$

And:

$$\frac{E\left[m\left(P\right)\right]}{E\left[P\right]}=\frac{E_{P}E_{\tilde{p}}\left[\tilde{p}|\tilde{p}\geq P\right]}{E\left[P\right]}-1$$

So, we wish to test whether

$$E_{P}E_{\tilde{p}}\left[\frac{\tilde{p}}{E\left[P\right]}|\tilde{p}\geq P\right]<^{?}E_{P}E_{\tilde{p}}\left[\frac{\tilde{p}}{P}|\tilde{p}\geq P\right]$$

or

$$E_{P}E_{\tilde{p}}\left[\frac{\tilde{p}}{P}-\frac{\tilde{p}}{E\left[P\right]}|\tilde{p}\geq P\right]>^{?}0$$

or

$$E_{P}E_{\tilde{p}\geq P}\left[\tilde{p}\left(\frac{1}{P}-\frac{1}{E\left[P\right]}\right)|\tilde{p}\geq P\right]>^{?}0$$

Note that once we've conditioned on $\tilde{p}\geq P$, we can replace $\tilde{p}$ with P and maintain an inequality

$$\begin{aligned}E_{P}E_{\tilde{p}\geq P}\left[\tilde{p}\left(\frac{1}{P}-\frac{1}{E\left[P\right]}\right)|\tilde{p}\geq P\right] &\geq E_{P}E_{\tilde{p}\geq P}\left[P\left(\frac{1}{P}-\frac{1}{E\left[P\right]}\right)|\tilde{p}\geq P\right]\\ &\geq E_{P}E_{\tilde{p}\geq P}\left[1-\frac{P}{E\left[P\right]}|\tilde{p}\geq P\right]\\ &\geq E_{P}\left[1-\frac{P}{E\left[P\right]}\right]\\ &\geq 0\end{aligned}$$

Which implies $cov\left(\frac{m(P)}{P},P\right)<0$.

Proof of Proposition.

Note that since $E\left[P|P\geq p\right]\geq p$,

$$\begin{aligned}E\left[T\left(P\right)\right] &= E_{p}\left[\frac{E\left[P|P\geq p\right]}{p}\frac{1-p}{1-E\left[P|P\geq p\right]}\right]\\ &\geq E_{p}\left[1+\frac{m\left(p\right)}{p}\right]\end{aligned}$$

So, it suffices to show that $E\left[\frac{m(P)}{P}\right]\geq\frac{E[m(P)]}{E[P]}$. Clearly

$$E\left[m\left(P\right)\right]=E\left[\frac{m\left(P\right)}{P}\right]E\left[P\right]+cov\left(P,\frac{m\left(P\right)}{P}\right)$$

so that

$$E\left[\frac{m\left(P\right)}{P}\right]=\frac{E\left[m\left(P\right)\right]-cov\left(P,\frac{m(P)}{P}\right)}{E\left[P\right]}$$

by Lemma 1, $cov\left(P,\frac{m(P)}{P}\right)\leq 0$. So,

$$E\left[\frac{m\left(P\right)}{P}\right]\geq\frac{E\left[m\left(P\right)\right]}{E\left[P\right]}=\frac{E\left[m\left(P\right)\right]}{\Pr\left\{U\right\}}$$

so that

$$E\left[T\left(P\right)\right]\geq E\left[1+\frac{m\left(P\right)}{P}\right]\geq 1+\frac{E\left[m\left(P\right)\right]}{\Pr\left\{U\right\}}$$

which is the desired result.

B.2 Specification for Point Estimation

I follow Hendren (2013) by assuming that $Z=P+\epsilon$, where ϵ has the following structure. With probability λ, individuals report a noisy measure of their true belief P that is drawn from a $[0,1]$-censored normal distribution with mean $P+\alpha\left(X\right)$ and variance σ^{2}. With this specification, $\alpha\left(X\right)$ reflects potential bias in elicitations and σ represents the noise. While this allows for general measurement error in the elicitations, it does not produce the strong focal point concentrations shown in Figure 1 and documented in existing work (Gan et al. (2005); Manski and Molinari (2010)). To capture these, I assume that with probability $1-\lambda$ individuals take their noisy report with the same bias $\alpha\left(X\right)$ and variance σ^{2}, but censor it into a focal point at 0, 50, or 100. If their elicitation would have been below κ, they report zero. If it would have been between κ and $1-\kappa$, they report 50; and if it would have been above $1-\kappa$, they report 1. Hence, I estimate four elicitation error parameters: $(\sigma, \lambda, \kappa, \alpha(X))$ that capture the patterns of noise and bias in the relationship between true beliefs, P, and the elicitations reported on the surveys, Z.[66]

Ideally, one would flexibly estimate the distribution of P given X at each possible value of X. This would enable separate estimates of the minimum pooled price ratio for each value of X. However, the dimensionality of X prevents this in practice. Instead, I again follow Hendren (2013) and adopt an index assumption on the cumulative distribution of beliefs, $F(p|X) = \int_0^p f_P(\tilde{p}|X)\, d\tilde{p}$,

$$F(p|X) = \tilde{F}(p|\Pr\{U|X\}) \tag{18}$$

where I assume $\tilde{F}(p|q)$ is continuous in q (where $q \in \{0,1\}$ corresponds to the level of $\Pr\{U|X\}$). This assumes that the distribution of private information is the same for two observable values, X and X', that have the same observable unemployment probability, $\Pr\{U|X\} = \Pr\{U|X'\}$. Although one could perform different dimension reduction techniques, controlling for $\Pr\{U|X\}$ is particularly appealing because it nests the null hypothesis of no private information ($F(p|X) = 1\{p \leq \Pr\{U|X\}\}$).[67]

A key difficulty with using functions to approximate the distribution of P is that much of the mass of the distribution is near zero. Continuous probability distribution functions, such as the Beta distributions used in Hendren (2013), require very high degrees for the shape parameters to acquire a good fit. Therefore, I approximate P as a sum of discrete point-mass distributions.[68] Formally, I assume

$$\tilde{F}(p|q) = w1\{p \leq q-a\} + (1-w)\Sigma_i \xi_i 1\{p \leq \alpha_i\}$$

where α_i are a set of point masses in $[0,1]$ and ξ_i is the mass on each point mass. I estimate these point mass parameters using maximum likelihood estimation. For the baseline results, I use 3 mass points, which generally provides a decent fit for the data. I then compute the pooled price ratio at each mass point and report the minimum across all values aside from the largest mass point. Mechanically, this has a value of $T(p) = 1$. As noted in Hendren (2013), estimation of the minimum $T(p)$ across the full support of the type distribution is not feasible because of an extremal quantile estimation problem. To keep the estimates "in-sample", I report values for the mean value of $q = \Pr\{U\} = 0.031$; but estimates at other values of q are similarly large.

C Welfare Metrics

C.1 Proof of Proposition 2

Note under state independence, the Euler equation implies

$$u'(c_{pre}(p)) = pu'(c_u(p)) + (1-p)u'(c_e(p))$$

[66]Specifically, the p.d.f./p.m.f. of Z given P is given by

$$f(Z|P,X) = \begin{cases} (1-\lambda)\Phi\left(\frac{-P-\alpha(X)}{\sigma}\right) + \lambda\Phi\left(\frac{\kappa-P-\alpha(X)}{\sigma}\right) & \text{if} \quad Z=0 \\ \lambda\left(\Phi\left(\frac{1-\kappa-P-\alpha(X)}{\sigma}\right) - \Phi\left(\frac{\kappa-P-\alpha(X)}{\sigma}\right)\right) & \text{if} \quad Z=0.5 \\ (1-\lambda)\Phi\left(\frac{1-P-\alpha(X)}{\sigma}\right) + \lambda\left(1-\Phi\left(\frac{1-\kappa-P-\alpha(X)}{\sigma}\right)\right) & \text{if} \quad Z=1 \\ \frac{1}{\sigma}\phi\left(\frac{Z-P-\alpha(X)}{\sigma}\right) & \text{if} \quad o.w. \end{cases}$$

where ϕ denotes the standard normal p.d.f. and Φ the standard normal c.d.f. I estimate four elicitation error parameters: $(\sigma, \lambda, \kappa, \alpha(X))$. σ captures the dispersion in the elicitation error, λ is the fraction of focal point respondents, κ is the focal point window. I allow the elicitation bias term, $\alpha(X)$, to vary with the observable variables, X. This allows elicitations to be biased, but maintains the assumption that true beliefs are unbiased.

This approach builds upon Manski and Molinari (2010) by thinking of the focal point responses as "interval data" (i.e. 50/50 corresponds to some region around 50%, but not exactly 50%). However, the present approach differs from Manski and Molinari (2010) by allowing the response to be a noisy and potentially biased measure of this response (as 50/50 corresponds to a region around 50% for the noisy Z measure, not the true P measure).

[67]Moreover, it allows the statistical model to easily impose unbiased beliefs, so that $\Pr\{U|X\} = E[P|X]$ for all X.

[68]This has the advantage that it does not require integrating over high degree of curvature in the likelihood function. In practice, it will potentially under-state the true variance in P in finite sample estimation. As a result, it will tend to produce lower values for $T(p)$ than would be implied by continuous probability distributions for P since the discrete approximation allows all individuals at a particular point mass to be able to perfectly pool together when attempting to cover the pooled cost of worse risks.

so that

$$u''\left(c_{pre}\left(p\right)\right)\frac{dc_{pre}}{dp}=u'\left(c_{u}\left(p\right)\right)-u'\left(c_{e}\left(p\right)\right)+pu''\left(c_{u}\left(p\right)\right)\frac{dc_{u}}{dp}+\left(1-p\right)u''\left(c_{e}\left(p\right)\right)\frac{dc_{e}}{dp}$$

Dividing,

$$u'\left(c_{pre}\left(p\right)\right)\frac{u''\left(c_{pre}\left(p\right)\right)}{u'\left(c_{pre}\left(p\right)\right)}\frac{dc_{pre}}{dp}=u'\left(c_{e}\right)\frac{u'\left(c_{u}\left(p\right)\right)-u'\left(c_{e}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}+pu'\left(c_{u}\left(p\right)\right)\frac{u''\left(c_{u}\left(p\right)\right)}{u'\left(c_{u}\left(p\right)\right)}\frac{dc_{u}}{dp}+\left(1-p\right)u'\left(c_{e}\left(p\right)\right)\frac{u''\left(c_{e}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}\frac{dc_{e}}{dp}$$

or

$$u'\left(c_{pre}\left(p\right)\right)\sigma\frac{-dlog\left(c_{pre}\right)}{dp}=u'\left(c_{e}\right)\sigma\left[log\left(c_{e}\right)-log\left(c_{u}\right)\right]+pu'\left(c_{u}\left(p\right)\right)\sigma\frac{-dlog\left(c_{u}\left(p\right)\right)}{dp}+\left(1-p\right)u'\left(c_{e}\left(p\right)\right)\sigma\frac{-dlog\left(c_{e}\left(p\right)\right)}{dp}$$

So, dividing by $u'\left(c_{e}\left(p\right)\right)$ yields:

$$\frac{u'\left(c_{pre}\left(p\right)\right)}{u'\left(c_{e}\right)}\sigma\frac{-dlog\left(c_{pre}\right)}{dp}=\sigma\left[log\left(c_{e}\right)-log\left(c_{u}\right)\right]+p\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}\sigma\frac{-dlog\left(c_{u}\left(p\right)\right)}{dp}+\left(1-p\right)\sigma\frac{-dlog\left(c_{e}\left(p\right)\right)}{dp}$$

And, using the Euler equation, $pu'\left(c_{u}\left(p\right)\right)+\left(1-p\right)u'\left(c_{e}\left(p\right)\right)=u'\left(c_{pre}\left(p\right)\right)$,

$$\begin{aligned}\frac{pu'\left(c_{u}\left(p\right)\right)+\left(1-p\right)u'\left(c_{e}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}\sigma\frac{-dlog\left(c_{pre}\left(p\right)\right)}{dp} &= \frac{u'\left(c_{u}\left(p\right)\right)-u'\left(c_{e}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}+p\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}\sigma\frac{-dlog\left(c_{u}\left(p\right)\right)}{dp}+\left(1-p\right)\sigma\frac{-dlog\left(c_{e}\left(p\right)\right)}{dp}\\ \left(p\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}+1-p\right)\sigma\frac{-dlog\left(c_{pre}\left(p\right)\right)}{dp} &= \frac{u'\left(c_{u}\left(p\right)\right)-u'\left(c_{e}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}+\left(p\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}+1-p\right)\sigma\frac{-dlog\left(c_{e}\left(p\right)\right)}{dp}+p\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}\sigma\left(\frac{d\left[log\left(c_{e}\right)-log\left(c_{u}\right)\right]}{dp}\right)\end{aligned}$$

so that

$$\sigma\frac{-dlog\left(c_{pre}\right)}{dp}=\frac{\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}-1}{1+p\left(\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}-1\right)}+\sigma\frac{-dlog\left(c_{e}\left(p\right)\right)}{dp}+\frac{p\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}}{p\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}+1-p}\sigma\left(\frac{d\left[log\left(c_{e}\right)-log\left(c_{u}\right)\right]}{dp}\right)$$

or

$$\frac{-dlog\left(c_{pre}\right)}{dp}=\frac{\frac{1}{\sigma}\left(\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}-1\right)}{1+p\left(\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}-1\right)}+\frac{-dlog\left(c_{e}\left(p\right)\right)}{dp}+\frac{p\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}}{p\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}+1-p}\left(\frac{d\left[log\left(c_{e}\right)-log\left(c_{u}\right)\right]}{dp}\right)$$

Note that the assumption is maintained that $log\left(c_{pre}\right)$ is linear in p, in addition to $log\left(c_{e}\right)$ and $log\left(c_{u}\right)$ being linear in p. This is of course an approximation in practice, as the equation above illustrates this cannot simultaneously be true for all p. Therefore, I assume it is true only in expectation, so that

$$\frac{-dlog\left(c_{pre}\right)}{dp}=\frac{1}{\sigma}\left(\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}-1\right)E\left[\frac{1}{1+p\left(\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}-1\right)}\right]+\frac{-dlog\left(c_{e}\left(p\right)\right)}{dp}+E\left[\frac{p\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}}{p\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}+1-p}\left(\frac{d\left[log\left(c_{e}\right)-log\left(c_{u}\right)\right]}{dp}\right)\right]$$

which if it holds for all p must also hold for the expectation taken with respect to p. Let $\kappa=E\left[\frac{1}{1+p\left(\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}-1\right)}\right]$.

Note also that

$$\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}-1\approx\sigma E\left[log\left(c_{e}\left(p\right)\right)-log\left(c_{u}\left(p\right)\right)\right]$$

which implies

$$\frac{-dlog\left(c_{pre}\right)}{dp}=E\left[log\left(c_{e}\left(p\right)\right)-log\left(c_{u}\left(p\right)\right)\right]\kappa+\frac{-dlog\left(c_{e}\left(p\right)\right)}{dp}+E\left[\frac{p\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}}{p\frac{u'\left(c_{u}\left(p\right)\right)}{u'\left(c_{e}\left(p\right)\right)}+1-p}\left(\frac{d\left[log\left(c_{e}\right)-log\left(c_{u}\right)\right]}{dp}\right)\right]$$

Now, consider the impact of unemployment on the first difference of consumption. Define Δ^{FD} as the estimated impact on the first difference in consumption:

$$\Delta^{FD}=E\left[log\left(c\right)-log\left(c_{-1}\right)|U=1\right]-E\left[log\left(c\right)-log\left(c_{-1}\right)|U=0\right]$$

Adding and subtracting $E\left[log\left(c_{e}\right)|U=1\right]$ yields

$$\Delta^{FD}=E\left[log\left(c\right)|U=1\right]-E\left[log\left(c_{e}\right)|U=1\right]+E\left[log\left(c_{e}\right)|U=1\right]-E\left[log\left(c\right)|U=0\right]-\left(E\left[log\left(c_{-1}\right)|U=1\right]-E\left[log\left(c_{-1}\right)|U=0\right]\right)$$

Note that $c=c_{u}$ for those with $U_{t}=1$ and $c=c_{e}$ for those with $U=0$. The following three equations help expand Δ^{FD}:

$$E\left[log\left(c_{-1}\right)|U=1\right]-E\left[log\left(c_{-1}\right)|U=0\right]=\frac{dlog\left(c_{pre}\right)}{dp}\frac{var\left(P\right)}{var\left(U\right)}$$

and

$$E\left[log\left(c\right)|U=1\right]-E\left[log\left(c_{e}\right)|U=0\right] = E\left[log\left(c_{u}\right)|U=1\right]-E\left[log\left(c_{e}\right)|U=1\right]$$
$$= E\left[log\left(c_{u}\right)-log\left(c_{e}\right)\right]+\frac{d\left[log\left(c_{u}\right)-log\left(c_{e}\right)\right]}{dp}\left(E\left[P|U=1\right]-E\left[P\right]\right)$$

and

$$E\left[log\left(c_{e}\right)|U=1\right]-E\left[log\left(c\right)|U=0\right] = E\left[log\left(c_{e}\right)|U=1\right]-E\left[log\left(c_{e}\right)|U=0\right]$$
$$= \frac{dlog\left(c_{e}\right)}{dp}\frac{var\left(P\right)}{var\left(U\right)}$$

So, substituting these into Δ^{FD} yields:

$$\Delta^{FD}=E\left[log\left(c_{u}\right)-log\left(c_{e}\right)\right]-\frac{var\left(P\right)}{var\left(U\right)}\left[\kappa\left(E\left[log\left(c_{e}\right)-log\left(c_{u}\right)\right]\right)+E\left[P\right]\frac{u'\left(c_{u}\right)}{u'\left(c_{e}\right)}\frac{d\left[log\left(c_{e}\right)-log\left(c_{u}\right)\right]}{dp}\right]+\left[\frac{d\left[log\left(c_{e}\right)-log\left(c_{u}\right)\right]}{dp}\right]\left(E\left[P|U=1\right]-E\left[P\right]\right)$$

Let $\frac{d\Delta}{dp}=\frac{d[log(c_e)-log(c_u)]}{dp}$ denote how the consumption drop varies with p. Solving for $E\left[log\left(c_{e}\right)-log\left(c_{e}\right)\right]$ yields

$$E\left[log\left(c_{u}\right)-log\left(c_{e}\right)\right]=\frac{\Delta^{FD}+\frac{d\Delta}{dp}\left(E\left[P|U=1\right]-E\left[P\right]\right)}{1-\frac{var(P)}{var(U)}\kappa-\bar{p}\sigma\frac{d\Delta}{dp}}$$

where κ =which yields the desired result. Note that if the consumption drop does not vary with p, then this reduces to

$$E\left[log\left(c_{u}\right)-log\left(c_{e}\right)\right]=\frac{\Delta^{FD}}{1-\frac{var(P)}{var(U)}\kappa}\equiv\Delta^{IV}$$

More generally, if the size of the consumption drop is increasing with p, then $E\left[log\left(c_{u}\right)-log\left(c_{e}\right)\right]>\Delta^{IV}$.

C.2 Ex-ante labor supply derivation

This section illustrates how to use the spousal labor supply response, combined with known estimates of the spousal labor response to labor earnings, to estimate the ex-ante willingness to pay for UI.

Spousal labor force participation generates income, y, but has an additively separable effort cost, $\eta\left(\theta\right)$. I assume a spouse labor supply decision, $l\in\{0,1\}$, is a binary decision and is contained in the set of other actions, a. Formally, let

$$\Psi\left(1-p,a,\theta\right)=\tilde{\Psi}\left(1-p,\tilde{a},\theta\right)+1\left\{l=1\right\}\eta\left(\theta\right)$$

where $\eta\left(\theta\right)$ is the disutility of labor for type θ, distributed F_{η} in the population.

Let $k\left(y,l,p\right)$ denote the utility value to a type p of choosing l to obtain income y when they face an unemployment probability of p. The labor supply decision is

$$k\left(y,1,p\right)-k\left(0,0,p\right)\geq\eta\left(\theta\right)$$

so that types will choose to work if and only if it increases their utility. This defines a threshold rule whereby individuals choose to work if and only if $\eta\left(\theta\right)\leq\bar{\eta}\left(y,p\right)$ and the labor force participation rate is given by $\Phi\left(y,p\right)=F\left(\bar{\eta}\left(y,p\right)\right)$.

Now, note that

$$\frac{d\Phi}{dp}=f\left(\bar{\eta}\right)\frac{\partial\bar{\eta}}{\partial p}=f\left(\bar{\eta}\right)\left[\frac{\partial k\left(y,1,p\right)}{\partial p}-\frac{\partial k\left(0,0,p\right)}{\partial p}\right]$$

and making an approximation that the impact of the income y does not discretely change the instantaneous marginal utilities (i.e. because it will be smoothed out over the lifetime or because the income is small), we have

$$\frac{d\Phi}{dp}\approx f\left(\bar{\eta}\right)\frac{\partial^{2}k}{\partial p^{2}}y$$

Finally, note that $\frac{\partial k}{\partial y}=v'\left(c_{pre}\left(p\right)\right)$ is the marginal utility of income. So,

$$\frac{d\Phi}{dp}\approx f\left(\bar{\eta}\right)\frac{d}{dp}\left[v'\left(c_{pre}\left(p\right)\right)\right]y$$

and integrating across all the types p yields

$$E_{p}\left[\frac{d\Phi}{dp}\right]\approx E_{p}\left[f\left(\bar{\eta}\right)\frac{d}{dp}v'\left(c_{pre}\left(p\right)\right)y\right]$$

To compare this response to a wage elasticity, consider the response to a \$1 increase in wages

$$\frac{d\Phi}{dy} = f(\bar{\eta}) \frac{\partial k}{\partial y}$$

so,

$$E_p \left[\frac{d\Phi}{dp} \right] \approx E_p \left[\frac{d\Phi}{dy} y \frac{\frac{d}{dp} v'(c_{pre}(p))}{v'(c_{pre}(p))} \right]$$

Now, let $\epsilon^{semi} = \frac{d\Phi}{dlog(y)}$ denote the semi-elasticity of spousal labor force participation. This yields

$$\frac{E_p \left[\frac{d\Phi}{dp} \right]}{\epsilon^{semi}} \approx E_p \left[\frac{\frac{d}{dp} v'(c_{pre}(p))}{v'(c_{pre}(p))} \right]$$

so that the ratio of the labor supply response to p divided by the semi-elasticity of labor supply with respect to wages reveals the average elasticity of the marginal utility function. Assuming this elasticity is roughly constant and noting that a Taylor expansion suggests that for any function $f(x)$, we have $\frac{f(1)-f(0)}{f(0)} \approx \frac{d}{dx} log(f)$,

$$\frac{E_p \left[\frac{d\Phi}{dp} \right]}{\epsilon^{semi}} \approx \frac{v'(1) - v'(0)}{v'(0)}$$

Now, how does one estimate $\frac{d\Phi}{dp}$? Regressing labor force participation, l, on Z will generate an attenuated coefficient because of measurement error in Z. If the measurement error is classical, one can inflate this by the ratio of the variance of Z to the variance of P, or

$$\frac{v'(1) - v'(0)}{v'(0)} \approx \beta \frac{1}{\epsilon^{semi}} \frac{var(Z)}{var(P)}$$

C.3 Derivation of W^{Social} as weighted average of $W^{Ex-ante}$ and $W^{Ex-post}$

This section shows that

$$W^{Social} \approx (1 - (E[P|U=1] - E[P|U=0])) W^{Ex-post} + (E[P|U=1] - E[P|U=0]) W^{Ex-ante}$$

under the assumption that $u = v$ and that $\frac{dlog(c_u)}{dp} = \frac{dlog(c_e)}{dp} = \frac{dlog(c_{post})}{dp}$

To begin, let $\bar{p} = E[p]$. Note that

$$\begin{aligned} W^{Social} + 1 &= \frac{E\left[\frac{p}{\bar{p}} u'(c_u)\right]}{E\left[\frac{1-p}{1-\bar{p}} u'(c_e)\right]} \\ &= \frac{E[u'(c_u)]}{E[u'(c_e)]} \frac{1 + cov\left(\frac{p}{\bar{p}}, \frac{u'(c_u)}{E[u'(c_u)]}\right)}{1 - cov\left(\frac{p}{1-\bar{p}}, \frac{u'(c_e)}{E[u'(c_e)]}\right)} \\ &\approx \frac{E[u'(c_u)]}{E[u'(c_e)]} \left(1 + cov\left(\frac{p}{\bar{p}}, \frac{u'(c_u)}{E[u'(c_u)]}\right) + cov\left(\frac{p}{1-\bar{p}}, \frac{u'(c_e)}{E[u'(c_e)]}\right)\right) \end{aligned}$$

where the last approximation follows from $\frac{1+x}{1-y} \approx 1 + x - y$ when x and y are small.

Now, let $\bar{c}_u = E[c_u]$ and $\bar{c}_e = E[c_e]$. Using a Taylor expansion for u' yields

$$\begin{aligned} cov\left(\frac{p}{\bar{p}}, \frac{u'(c_u)}{E[u'(c_u)]}\right) &= cov\left(\frac{p}{\bar{p}}, \frac{u'(\bar{c}_u) + u''(\bar{c}_u)(c_u - \bar{c}_u)}{u'(\bar{c}_u)}\right) \\ &\approx -\sigma cov\left(\frac{p}{\bar{p}}, \frac{(c_u - \bar{c}_u)}{\bar{c}_u}\right) \\ &\approx -\sigma cov\left(\frac{p}{\bar{p}}, log(c_u)\right) \\ &\approx -\sigma \frac{var(p)}{\bar{p}} \frac{dlog(c_u)}{dp} \end{aligned}$$

Similarly,

$$cov\left(\frac{p}{1-\bar{p}}, \frac{u'(c_e)}{E[u'(c_e)]}\right) \approx -\sigma \frac{var(p)}{1-\bar{p}} \frac{dlog(c_e)}{dp}$$

So that

$$cov\left(\frac{p}{\bar{p}},\frac{u'(c_u)}{E[u'(c_u)]}\right)+cov\left(\frac{p}{1-\bar{p}},\frac{u'(c_e)}{E[u'(c_e)]}\right)\approx-\sigma\frac{var(p)}{\bar{p}(1-\bar{p})}\frac{dlog(c_e)}{dp}+\frac{1}{\bar{p}}\left(\frac{d[log(c_e)-log(c_u)]}{dp}\right)$$

and note

$$\frac{var(p)}{\bar{p}(1-\bar{p})}=E[P|U=1]-E[P|U=0]$$

Therefore,

$$cov\left(\frac{p}{\bar{p}},\frac{u'(c_u)}{E[u'(c_u)]}\right)+cov\left(\frac{p}{1-\bar{p}},\frac{u'(c_e)}{E[u'(c_e)]}\right)\approx\sigma\frac{-dlog(c_e)}{dp}(E[P|U=1]-E[P|U=0])+\frac{1}{\bar{p}}\frac{d[log(c_e)-log(c_u)]}{dp}$$

Now, Section C.1 shows that the Euler equation implies

$$\frac{-dlog(c_{pre})}{dp}=E[log(c_e(p))-log(c_u(p))]\kappa+\frac{-dlog(c_e(p))}{dp}+E\left[\frac{p\frac{u'(c_u(p))}{u'(c_e(p))}}{p\frac{u'(c_u(p))}{u'(c_e(p))}+1-p}\left(\frac{d[log(c_e)-log(c_u)]}{dp}\right)\right]$$

so that

$$cov\left(\frac{p}{\bar{p}},\frac{u'(c_u)}{E[u'(c_u)]}\right)+cov\left(\frac{p}{1-\bar{p}},\frac{u'(c_e)}{E[u'(c_e)]}\right)\approx$$

$$\sigma\left[\frac{-dlog(c_{pre})}{dp}-E[log(c_e)-log(c_u)]-E\left[\frac{p\frac{u'(c_u(p))}{u'(c_e(p))}}{p\frac{u'(c_u(p))}{u'(c_e(p))}+1-p}\left(\frac{d[log(c_e)-log(c_u)]}{dp}\right)\right]\right](E[P|U=1]-E[P|U=0])+\frac{1}{\bar{p}}\frac{d[log(c_e)-log(c_u)]}{dp}$$

or

$$cov\left(\frac{p}{\bar{p}},\frac{u'(c_u)}{E[u'(c_u)]}\right)+cov\left(\frac{p}{1-\bar{p}},\frac{u'(c_e)}{E[u'(c_e)]}\right)\approx$$

$$\sigma\left[\frac{-dlog(c_{pre})}{dp}-E[log(c_e)-log(c_u)]\right](E[P|U=1]-E[P|U=0])+\frac{1}{\bar{p}}\left(1-\sigma\frac{var(P)}{(1-\bar{p})}E\left[\frac{p\frac{u'(c_u(p))}{u'(c_e(p))}}{p\frac{u'(c_u(p))}{u'(c_e(p))}+1-p}\right]\right)\frac{d[log(c_e)-log(c_u)]}{dp}$$

or

$$cov\left(\frac{p}{\bar{p}},\frac{u'(c_u)}{E[u'(c_u)]}\right)+cov\left(\frac{p}{1-\bar{p}},\frac{u'(c_e)}{E[u'(c_e)]}\right)\approx$$

$$\left(W^{Ex-ante}-W^{Ex-post}\right)(E[P|U=1]-E[P|U=0])+\frac{1}{\bar{p}}\left(1-\sigma\frac{var(P)}{(1-\bar{p})}E\left[\frac{p\frac{u'(c_u(p))}{u'(c_e(p))}}{p\frac{u'(c_u(p))}{u'(c_e(p))}+1-p}\right]\right)\frac{d[log(c_e)-log(c_u)]}{dp}$$

So, if $\frac{d[log(c_e)-log(c_u)]}{dp}=0$, then

$$cov\left(\frac{p}{\bar{p}},\frac{u'(c_u)}{E[u'(c_u)]}\right)+cov\left(\frac{p}{1-\bar{p}},\frac{u'(c_e)}{E[u'(c_e)]}\right)\approx\left(W^{Ex-ante}-W^{Ex-post}\right)(E[P|U=1]-E[P|U=0])$$

Additionally, note that

$$\begin{aligned}\frac{E[u'(c_u)]}{E[u'(c_e)]}&\approx1+\sigma\frac{\bar{c}_e-\bar{c}_u}{\bar{c}_e}\\&\approx1+\sigma(E[log(c_e)-log(c_u)])\end{aligned}$$

Combining, we have

$$W^{Social}+1\approx(1+\sigma(E[log(c_e)-log(c_u)]))\left(1+\sigma\left[\frac{-dlog(c_{pre})}{dp}-E[log(c_e)-log(c_u)]\right]\frac{var(P)}{var(U)}\right)$$

So that if $\frac{d[log(c_e)-log(c_u)]}{dp}=0$,

$$1+W^{Social}\approx\left(1+W^{Ex-post}\right)\left(1+\frac{var(P)}{var(U)}\left[W^{Ex-ante}-W^{Ex-post}\right]\right)$$

Now, approximating $(1+x)(1+y)\approx1+x+y$ yields

$$W^{Social}\approx\left(1-\frac{var(P)}{var(U)}\right)W^{Ex-post}+\frac{var(P)}{var(U)}W^{Ex-ante}$$

More generally, if $\frac{d[log(c_e)-log(c_u)]}{dp} \neq 0$, then

$$W^{Social} \approx \left(1-\frac{var\,(P)}{var\,(U)}\right) W^{Ex-post} + \frac{var\,(P)}{var\,(U)} W^{Ex-ante} + \frac{1}{\bar{p}}\left(1-\sigma\frac{var\,(P)}{(1-\bar{p})}E\left[\frac{p\frac{u'(c_u(p))}{u'(c_e(p))}}{p\frac{u'(c_u(p))}{u'(c_e(p))}+1-p}\right]\right)\frac{d\left[log\,(c_e)-log\,(c_u)\right]}{dp}$$

Note that the value of $\frac{1}{\bar{p}}\left(1-\sigma\frac{var(P)}{(1-\bar{p})}E\left[\frac{p\frac{u'(c_u(p))}{u'(c_e(p))}}{p\frac{u'(c_u(p))}{u'(c_e(p))}+1-p}\right]\right)\frac{d[log(c_e)-log(c_u)]}{dp}$, which generally will take on the same sign as the impact of p on the consumption drop, $\frac{d[log(c_e)-log(c_u)]}{dp}$, as long as $\sigma < \frac{1-\bar{p}}{var(P)E\left[\frac{p\frac{u'(c_u(p))}{u'(c_e(p))}}{p\frac{u'(c_u(p))}{u'(c_e(p))}+1-p}\right]}$, where the denominator is extremely small in our case. Intuitively, if higher values of p correspond to bigger consumption drops, then the social willingness to pay is lower than is implied by the average willingness to pay measures, $W^{Ex-post}$ and $W^{Ex-ante}$.

C.4 Modified Baily-Chetty Condition

Proof of Proposition 3 To see this, note that the optimal allocation solves the first order condition:

$$\frac{\partial V}{\partial b}+\frac{\partial V}{\partial \tau}\frac{d\tau}{db}=0$$

where

$$\frac{d\tau}{db}=\frac{E\left[p\left(\theta\right)\right]}{1-E\left[p\left(\theta\right)\right]}+\frac{d}{db}\left[\tau\frac{E\left[p\left(\theta\right)\right]}{1-E\left[p\left(\theta\right)\right]}+T\left(a\left(\theta\right)\right)\right]$$

is the increased premium required to cover the cost of additional benefits, which includes the impact of the behavioral response, $\frac{d}{db}\left[\tau\frac{E[p]}{1-E[p]}+T\left(a\left(\theta\right)\right)\right]$. Note this includes the response from additional unemployment entry (e.g. $\frac{dE[p]}{db}$) and through any other behavioral response through changes in the choice of $a\left(\theta\right)$. Also, note these responses are "policy responses" as defined in Hendren (2015) – they are the behavioral response to a simultaneous increase in b and τ in a manner for which the government's budget breaks even.

Now, one can recover the partial derivatives using the envelope theorem:

$$\frac{\partial V}{\partial b}=E\left[p\left(\theta\right)u'\left(c_u\left(\theta\right)\right)\right]$$

$$\frac{\partial V}{\partial \tau}=-E\left[\left(1-p\left(\theta\right)\right)v'\left(c_e\left(\theta\right)\right)\right]$$

So, the optimality condition becomes:

$$\frac{E\left[\frac{p(\theta)}{E[p(\theta)]}u'\left(c_u\left(\theta\right)\right)\right]}{E\left[\frac{(1-p(\theta))}{E[1-p(\theta)]}v'\left(c_e\left(\theta\right)\right)\right]}=1+FE$$

where

$$FE=\frac{\frac{d}{db}\left[\tau\frac{E[p(\theta)]}{1-E[p(\theta)]}+N\left(a\left(\theta\right)\right)\right]}{\frac{E[p(\theta)]}{1-E[p(\theta)]}}$$

If only p is the margin of adjustment, then

$$FE=\tau\frac{\frac{d}{db}\left[\frac{E[p(\theta)]}{1-E[p(\theta)]}\right]}{\frac{E[p(\theta)]}{1-E[p(\theta)]}}=\frac{\epsilon_{p,b}}{1-E\left[p\left(\theta\right)\right]}$$

where $\epsilon_{p,b}$ is the elasticity of the unemployment probability with respect to the benefit level. More generally one would need to incorporate the fiscal externality associated with the responses from a (e.g. wages).

APPENDIX TABLE I

Alternative Lower Bound Specifications

Specification:	Baseline	Linear (vs Probit)	Alternative Aggregation Windows			Alternative Subj. Prob Spec		Alternative Outcomes		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$E[T_Z(P_Z)-1]$	**0.7687**	**0.6802**	**0.7716**	**0.7058**	**0.7150**	**0.7462**	**0.7681**	**0.5296**	**0.3675**	**0.5790**
s.e.	**(0.058)**	**(0.051)**	**(0.05)**	**(0.048)**	**(0.048)**	**(0.051)**	**(0.054)**	**(0.033)**	**(0.04)**	**(0.086)**
$E[m_Z(P_Z)]$	0.0239	0.0209	0.0237	0.0217	0.0220	0.0229	0.0236	0.0314	0.0147	0.0067
s.e.	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.001)
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Pr{U=1}	0.0310	0.0307	0.0307	0.0307	0.0307	0.0307	0.0307	0.0593	0.0401	0.0115
Controls										
Demographics	X	X	X	X	X	X	X	X	X	X
Job Characteristics	X	X	X	X	X	X	X	X	X	X
Elicitation Specification										
Polynomial Degree	3	3	3	3	3	1	4	3	3	3
Focal pt dummies (0, 50, 100)	X	X	X	X	X	X	X	X	X	X
Aggregation Window	Age x Gender	Age x Gender	Constant	Age x Gender x Industry	Age x Gender x Occupation	Age x Gender	Age x Gender	Age x Gender	Age x Gender	Age x Gender
Unemployment Outcome Window	12 months	12 months	12 months	12 months	12 months	12 months	12 months	24 months	6-24 months	6-12 months
Error Specification	Probit	Linear	Probit	Probit	Probit	Probit	Probit	Probit	Probit	Probit
Num of Obs.	25516	26640	26640	26640	26640	26640	26640	26640	26640	26640
Num of HHs	3467	3467	3467	3467	3467	3467	3467	3467	3467	3467

Notes: Table reports robustness of lower bound estimates in Table II to alternative specifications. Column (1) replicates the baseline specification in Table II (Column (1)). Column (2) constructs the predicted values, Pr{U|X,Z}, using a linear model instead of a probit specification. Columns (3)-(5) consider alternative aggregation windows for translating the distribution of predicted values into estimates of $E[m_Z(P_Z)]$. While Column (1) constructs $m_Z(P_Z)$ using the predicted values within age-by-gender groups, Column (3) aggregates the predicted values across the entire sample. Column (4) uses a finer partition, aggregating within age-by-gender-by-industry groups. Column (5) aggregates within age-by-gender-by-occupation groups. Columns (6)-(7) consider alternative specifications for the subjective probability elicitations. Column (6) uses only a linear specification in Z combined with focal point indicators at Z=0, Z=50, and Z=100, as opposed to the baseline specification that also includes a polynomial in Z. Column (7) adds a third and fourth order polynomial in Z to the baseline specification. Columns (8)-(10) consider alternative outcome definitions for U. Column (8) defines unemployment, U, as an indicator for involuntary job loss at any point in between survey waves (24 months). Column (9) defines unemployment as an indicator for job loss in between survey waves excluding the first six months after the survey (i.e. 6-24 months). Finally, Column (10) defines unemployment as an indicator for job loss in the 6-12 months after the survey wave.

APPENDIX TABLE II

Estimation of F(p|X)

Specification	Baseline	Alternative Controls: Demo	Alternative Controls: Health	Sub-Samples: Age <= 55	Sub-Samples: Age > 55	Below Median Wage	Above Median Wage	Tenure > 5 yrs	Tenure <= 5 yrs
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1st mass									
Location	0.001	0.012	0.002	0.001	0.002	0.007	0.000	0.000	0.022
s.e.	(0.001)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.001)	(0.000)	(0.003)
Weight	0.446	0.713	0.449	0.437	0.461	0.530	0.452	0.422	0.612
s.e.	(0.024)	(0.071)	(0.054)	(0.035)	(0.030)	(0.032)	(0.034)	(0.036)	(0.034)
T(p)	63.839	6.301	39.032	101.038	36.986	12.413	262.088	6.9E+08	5.052
s.e.	6.1E+06	1.7E+00	1.8E+06	1.0E+07	1.1E+06	3.2E+00	7.6E+07	2.5E+08	6.0E-01
2nd mass									
Location	0.031	0.031	0.032	0.030	0.031	0.037	0.024	0.018	0.0575
s.e.	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Weight	0.471	0.202	0.470	0.483	0.456	0.365	0.486	0.508	0.2771
s.e.	(0.024)	(0.071)	(0.052)	(0.035)	(0.030)	(0.032)	(0.034)	(0.037)	(0.0341)
T(p)	4.360	8.492	4.228	4.325	4.442	5.217	4.223	5.736	4.7392
s.e.	0.203	4.194	4.576	0.306	0.279	0.417	2.181	3.008	0.5227
3rd Mass									
Location	0.641	0.639	0.642	0.639	0.643	0.626	0.649	0.641	0.6420
s.e.	(0.004)	(0.004)	(0.028)	(0.005)	(0.005)	(0.005)	(0.006)	(0.005)	(0.0055)
Weight	0.082	0.086	0.081	0.081	0.083	0.105	0.061	0.070	0.1105
s.e.	(0.002)	(0.002)	(0.006)	(0.003)	(0.003)	(0.003)	(0.003)	(0.002)	(0.0040)
Controls									
Demographics	X	X	X	X	X	X	X	X	X
Job Characteristics	X		X	X	X	X	X	X	X
Health Characteristics			X						
Num of Obs.	26,640	26,640	22,831	11,134	15,506	13,320	13,320	17,850	8,790
Num of HHs	3,467	3,467	3,180	2,255	3,231	2,916	2,259	2,952	2,437

Notes: This table presents estimates of the distribution of private information about unemployment risk, P. Column (1) reports the baseline specification. Columns (2) uses only demographic controls; Column (3) uses demographic, job characteristics, and health characteristics. Columns (4)-(9) report results for the baseline specification on various subsamples including below and above age 55 (Columns 4 and 5), above and below-median wage earners (Columns 6 and 7) and above and below 5 years of job tenure. The F(p) estimates report the location and mass given to each point mass, evaluated at the mean q=Pr{U=1}=0.031. For example, in the baseline specification, the results estimate a point mass at 0.001, 0.031, and 0.641 with weights 0.446, 0.471 and 0.082. The values of T(p) represent the markup that individuals at this location in the distribution would have to be willing to pay to cover the pooled cost of worse risks. All parameter estimates are constructed using maximum likelihood. Because of the non-convexity of the optimization program, I assess the robustness to 1000 initial starting values. All standard errors are constructed using bootstrap re-sampling using 1000 re-samples at the household level.

APPENDIX TABLE III

Summary Statistics (PSID Sample)

	mean	std dev
Variable		
Age	39.749	10.24
Male	0.810	0.39
Unemployment	0.057	0.23
Year	1985	7.66
Log Consumption	8.204	0.65
Log Expenditure Needs	8.125	0.32
Consumption growth $(\log(c_{t-2})-\log(c_{t-1}))$	0.049	0.358
Sample Size		
Number of Observations	79,312	
Number of Households	11,006	

Notes: This table presents the summary statistics for the PSID sample used to estimate the impact of future unemployment on consumption growth in the year prior to unemployment. I use data from the PSID for years 1971-1997. Sample includes all household heads with non-missing variables.

APPENDIX TABLE IV

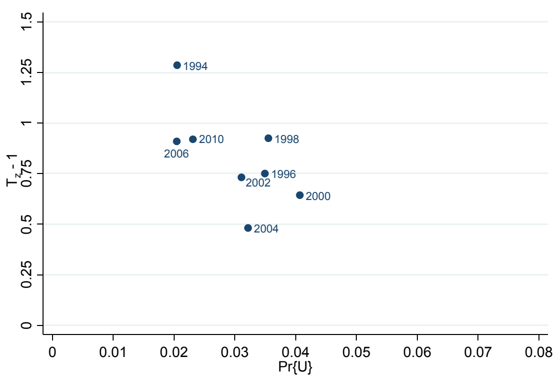
Information Realization Between t-2 and t-1 ("First Stage")

	Full Sample	Male	Female	Age > 55	Age <= 55	Year <= 1997	Year > 1997	Male, Age <= 55, Year <= 1997
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(7)
Dependent Variable:								
Unemp (Next 12 months)	0.1968	0.1956	0.1978	0.2079	0.1806	0.2316	0.1829	0.2089
s.e.	0.0121	0.0191	0.0168	0.0154	0.0192	0.0244	0.0134	0.0627
Unemp (12-24 months)	0.0937	0.0613	0.1199	0.0893	0.0994	0.1080	0.0847	0.0454
s.e.	0.0121	0.0191	0.0168	0.0154	0.0192	0.0244	0.0134	0.0627
Difference	0.1031	0.1343	0.0779	0.1186	0.0812	0.1236	0.0982	0.1635
bootstrap s.e.	0.0121	0.0191	0.0168	0.0154	0.0192	0.0244	0.0134	0.0627
Num of Obs.	26,640	10,740	15,900	15,506	11,134	8,571	18,069	1,210

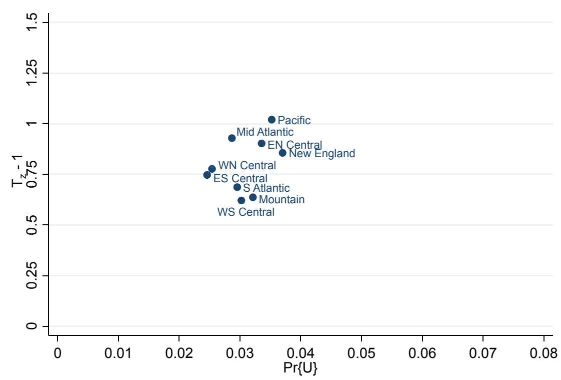
Note: This table presents estimates from regressions of the elicitation, Z, on unemployment measured in both (a) the subsequent 12 months and (b) the subsequent 12-24 months. The first row corresponds to the first stage for the ex-post welfare measure; the final row ("Difference") corresponds to the first stage for the ex-ante welfare measure. Column (1) uses the baseline HRS sample. Columns (2)-(7) explore the heterogeneity in the estimates by subgroup. Columns (2)-(3) restrict the sample to males and females.Columns (4)-(5) restrict the sample to those above and below age 55. Columns (6)-(7) restrict the sample to before and after 1997. Standard errors are computed using 500 bootstrap repetitions resampling at the household level.

ONLINE APPENDIX FIGURE I: Additional Lower Bounds on $E\left[T\left(P\right)\right]$

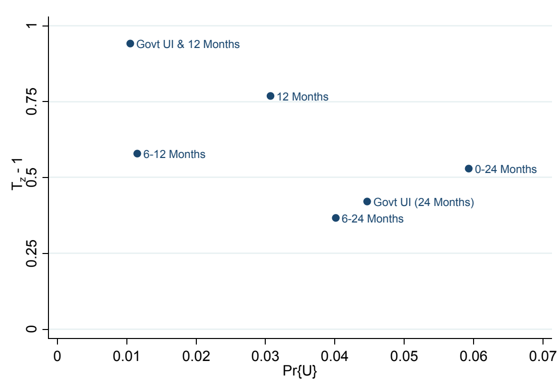
A. By Year



B. By Census Division

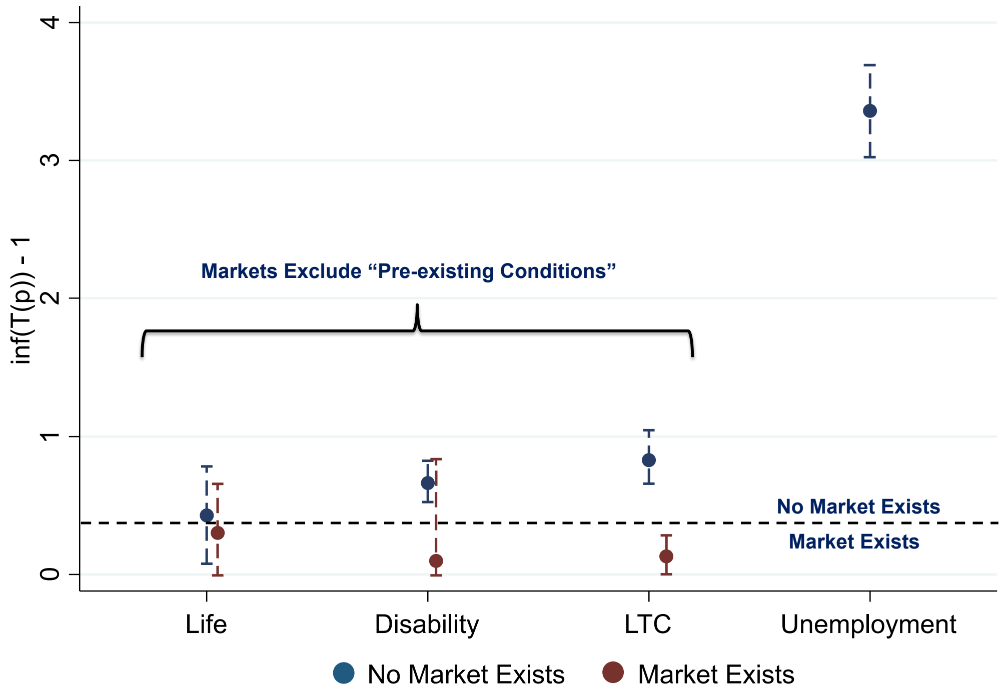


C. Alternative U definitions



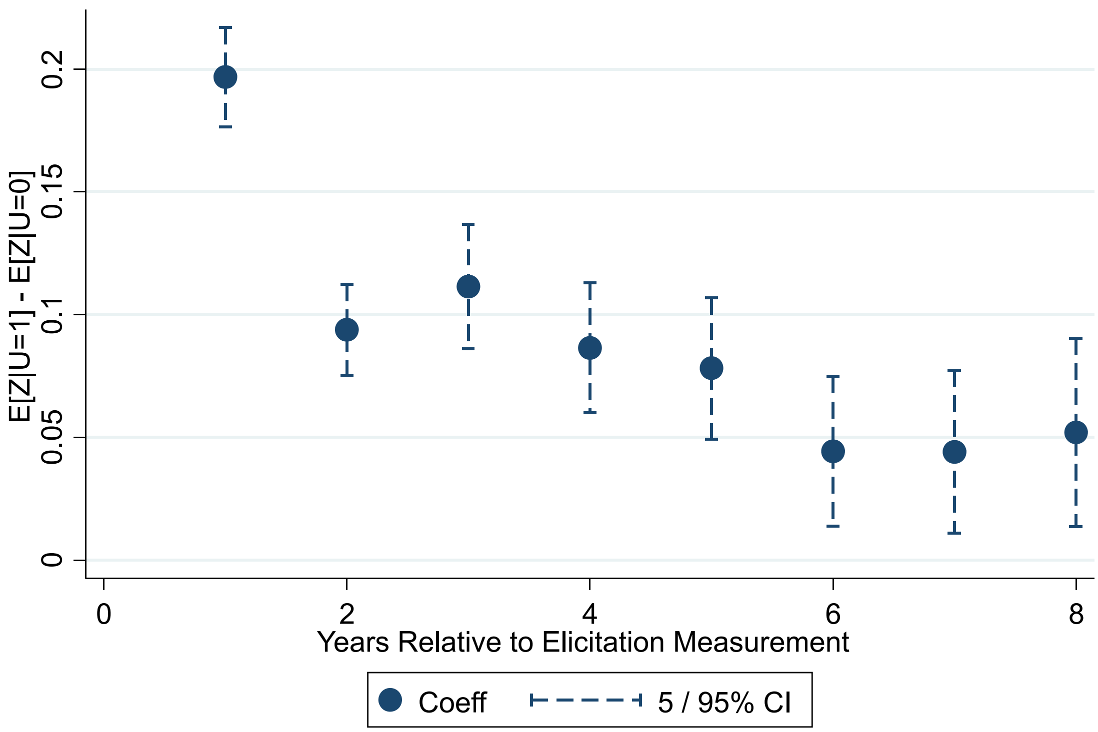
Notes: This figure presents additional estimates of the lower bound on the average pooled price ratio, $E\left[T_Z\left(P_Z\right)\right]$. Panel A reports separate estimates for each wave of the survey and Panel B reports estimates by census division. Panel C reports a set of estimates that use alternative definitions of U. This includes an indicator for involuntarily losing one's job for three time windows: in between surveys (0-24 months), in the 6-12 months after the survey, and 6-24 months after the survey. The 6-12 and 6-24 month specifications simulate lower bounds on $E\left[T_Z\left(P_Z\right)\right]$ in a hypothetical underwriting scenario whereby insurers would impose 6 month waiting periods. I also include specifications that interact these indicators with indicators that the individual had positive government UI claims, which effectively restricts to the subset of unemployment spells where the individual takes up government UI benefits.

ONLINE APPENDIX FIGURE II: Comparison to Other Non-Existing Insurance Markets



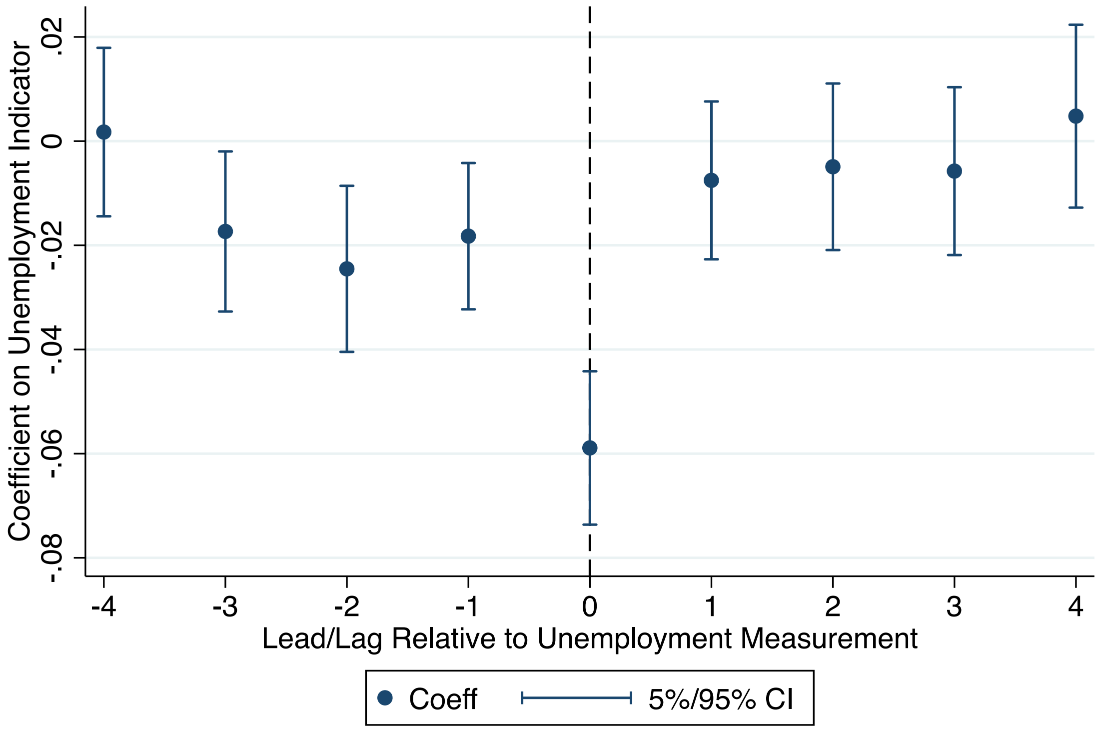
Notes: Hendren (2013) argues private information prevents people with pre-existing conditions from purchasing insurance in LTC, Life, and Disability insurance markets. This figure compares the estimates of $\inf T(p) - 1$ for the baseline specification in the unemployment context to the estimates in Hendren (2013) for the sample of individuals who are unable to purchase insurance due to a pre-existing condition (blue circles) and those whose observables would allow them to purchase insurance in each market (red hollow circles). Figure reports the confidence interval and the 5 / 95% confidence interval for each estimate in each sample. For the sub-samples in LTC, Life, and Disability for which the market exists, one cannot reject the null hypothesis of no private information, $\inf T(p) = 0$. In contrast, sub-samples whose observables would prevent them from purchasing insurance tend to involve larger estimates of the minimum pooled price ratio, which suggests the frictions imposed by private information form the boundary of the existence of insurance markets.

ONLINE APPENDIX FIGURE III: "First Stage" Impact of Unemployment on Beliefs



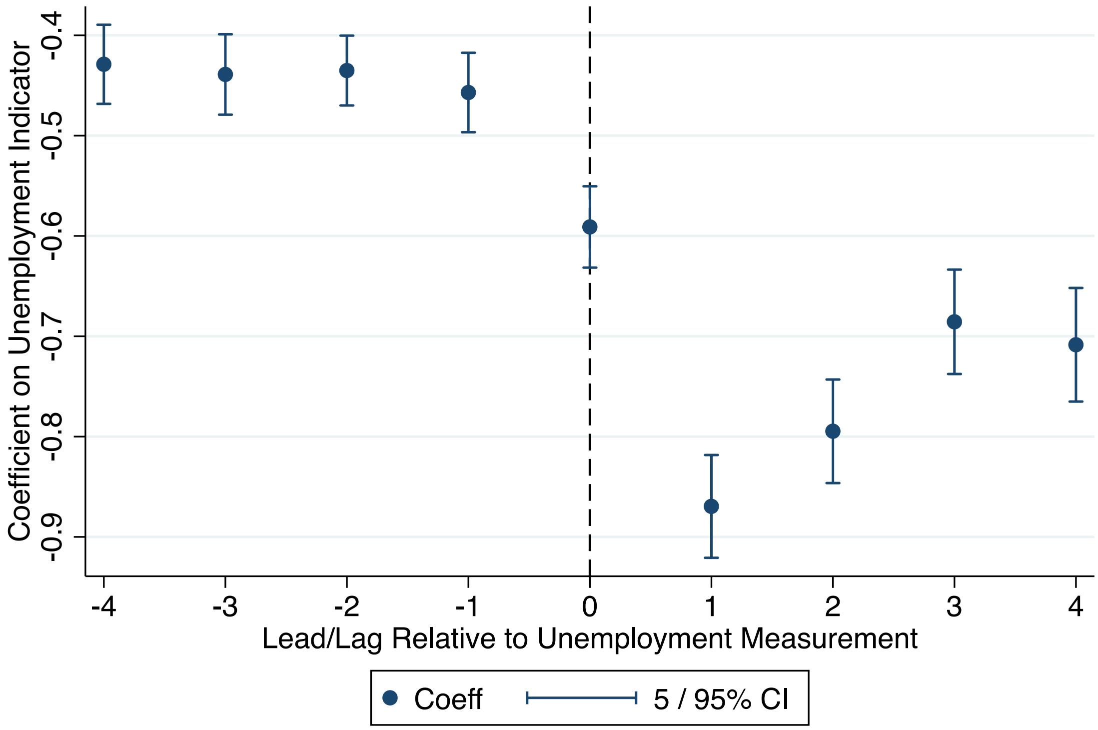
Notes: This figure presents the estimated coefficients of a regression of the elicitations (elicited in year t) on unemployment indicators in year $t+j$ for $j = 1, .., 8$. To construct the unemployment indicators for each year $t+j$, I construct an indicator for involuntary job loss in any survey wave (occuring every 2 years). I then use the data on when the job loss occured to assign the job loss to either the first or second year in between the survey waves. Because of the survey design, this definition potentially misses some instances of involuntary separation that occur in back-to-back years in between survey waves. To the extent to which such transitions occur, the even-numbered years in the Figure are measured with greater measurement error. The figure presents estimated 5/95% confidence intervals using standard errors clustered at the household level.

ONLINE APPENDIX FIGURE IV: Impact of Job Loss on Consumption



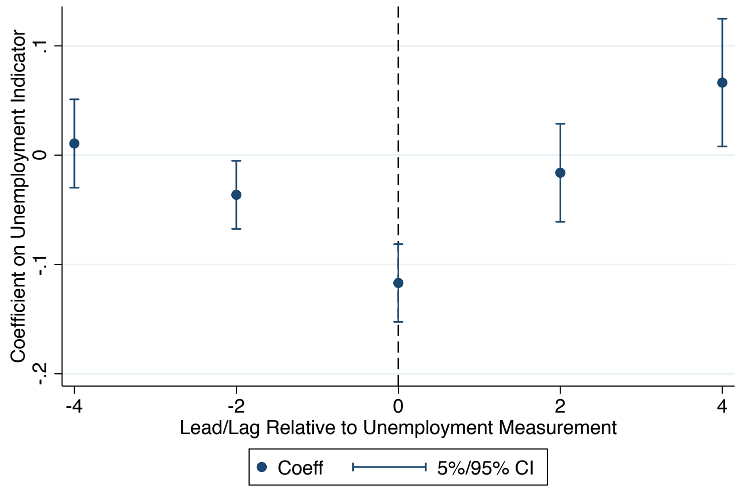
Notes: This figure re-constructs the analysis in Figure IV using job loss instead of unemployment. I define job loss as an indicator for being laid off or fired from the job held in the previous wave of the survey. The figure present coefficients from separate regressions of leads and lags of the log change in food expenditure on an indicator of job loss, along with controls for year indicators and a cubic in age. Sample is restricted to household heads who did not lose their job in $t-1$ or $t-2$.

ONLINE APPENDIX FIGURE V: Household Income Pattern Around Unemployment



Notes: This figure presents the estimated coefficients of a regression of leads and lags of log household income on an indicator for unemployment. The figure replicates the sample and specification in Figure IV (Panel B) by replacing the dependent variable with log household income as opposed to the change in log food expenditure. I restrict the sample to household heads who are not unemployed in $t-1$ or $t-2$.

ONLINE APPENDIX FIGURE VI: Impact of Unemployment on Total Consumption Expenditure (2-year intervals)



Notes: This figure presents the estimated coefficients of a regression of leads and lags of log household consumption expenditure on an indicator for unemployment. The figure replicates the sample and specification in Figure IV (Panel B) by replacing the dependent variable with log total consumption expenditure on a sample beginning in 1999, surveyed every two years. I restrict the sample to household heads who are not unemployed in $t-2$ or $t-4$. Following the specification in Figure IV (Panel B), the sample is restricted to observations with less than a threefold change in consumption expenditures. Post 1999, the PSID asks a broader set of consumption questions but is conducted every two years, which prevents analyzing total 1-year interval responses to unemployment.