Knowledge of Future Job Loss and Implications for Unemployment Insurance

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Abstract

This paper studies the positive and normative implications of individuals’ knowledge about their potential future job loss. Using information contained in subjective probability elicitations, I show individuals have significant information about their chances of losing their job conditional on a wide range of observable information insurers could potentially use to price the insurance. Lower bounds suggest individuals would need to be willing to pay at least a 75% markup to generate a profitable private unemployment insurance market; semi-parametric point estimates place this markup in excess of 300%.

In response to learning about future unemployment, individuals decrease consumption and spouses are more likely to enter the labor market. The presence of knowledge about future unemployment introduces a bias in existing methods to estimate the willingness to pay for UI but also generates new measurement methods that exploit this response to learning. From a positive perspective, estimates of the willingness to pay are all below the markups imposed by adverse selection, suggesting that private information about future job loss provides a micro-foundation for the absence of a private unemployment insurance market. From a normative perspective, my results suggest previous literature understates the value of social insurance because UI insures not only the realization of unemployment but also the risk of future unemployment.

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1 Introduction

The risk of losing one’s job is one of the most salient risks faced by working-age individuals. Job loss leads to drops in consumption and significant welfare losses.\(^1\) Millions of people hold life insurance, health insurance, liability insurance, and many other insurance policies.\(^2\) Why isn’t there an analogous thriving market for insurance against losing one’s job?\(^3\)

The government is heavily involved in providing unemployment insurance (UI) benefits, and there is a large literature characterizing the optimal amount of these benefits.\(^4\) Yet it is not clear what market failures, if any, provide a rationale for government intervention. If there is a welfare improvement from additional UI, why can’t private firms provide such benefits? If knowledge about future unemployment creates a wedge between what the government and private markets can do, does this micro-foundation alter the characterization of the optimal amount of UI benefits?

This paper provides empirical evidence that unemployment or job loss insurance would be too adversely selected to deliver a positive profit, at any price. Moreover, the presence of knowledge about future unemployment prospects changes the calculus describing the utilitarian-optimal unemployment insurance benefit level and yields new empirical strategies for its estimation.

I begin by developing the argument that private information prevents the existence of a private UI market. I provide a theory for when a UI market can exist and use the model to derive the empirical estimands of interest. Individuals may have private information about their future unemployment prospects, and insurance may increase their likelihood of unemployment (i.e. moral hazard). In this environment, a private market cannot exist unless someone is willing to pay the markup over actuarially fair premiums required to cover the cost of those with higher

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\(^1\)See Gruber (1997), Browning and Crossley (2001), Aguiar and Hurst (2005), Chetty (2008), and Blundell et al. (2012) among others.

\(^2\)60% of people in the US have insurance against damaging their cell phones and 1.4 million pets have health insurance in North America (see http://www.warrantyweek.com/archive/ww20131114.html and http://www.embracepetinsurance.com/pet-industry/pet-insurance/statistics).

\(^3\)In terms of private companies selling unemployment or job loss insurance, 2 companies have attempted to sell such policies in the past 20 years. PayCheck Guardian attempted to sell policies from 2008-2009, but stopped selling in 2009 with industry consultants arguing “The potential set of policyholders are selecting against the insurance company, because they know their situation better than an insurance company might” (http://www.nytimes.com/2009/08/08/your-money/08money.html). More recently, IncomeAssure has partnered with states to offer top-up insurance up to a 50% replacement rate for workers in some industries and occupations (https://www.incomeassure.com). Back-of-the-envelope calculations suggest their markups exceed 500% over actuarially fair prices. Indeed, it has been criticized for not saliently noting in its sales process that the government provides the baseline 30-40% replacement rate, shrouding the true price of the insurance (e.g. http://www.mlive.com/jobs/index.ssf/2011/08/get_out_your_calculator_before_you_buy_p.html#).

\(^4\)See, for example, Baily (1976); Gruber (1997); Chetty (2008); Landais (2015) among many others.
probabilities of unemployment adversely selecting their contract.\textsuperscript{5}

I use the information contained in subjective probability elicitations from the Health and Retirement Survey to identify lower bounds and point estimates for these markups, building on the approach of Hendren (2013b). Individuals are asked “what is the percent chance (0-100) that you will lose your job in the next 12 months?”. I do not assume individuals necessarily report their true beliefs that govern behavior; rather, I combine the elicitations with ex-post information about whether the individual actually loses her job to infer properties of the distribution of beliefs in the population. Individuals have private information if their elicitations predict their future job loss conditional on the observable characteristics insurers would use to price the insurance contracts, such as industry, occupation, demographics, unemployment history, etc.

Across a wide range of specifications, I find individuals hold a significant amount of private information that is not captured by the large set of observable characteristics available in the HRS. I use the distribution of predicted values of unemployment given the elicitations to yield a lower bound of 70\% on the markup individuals would have to be willing to pay to cover the cost of higher risks adversely selecting their contract. The presence of this private information is consistent across subsamples: old and young, long and short job tenure, industries and occupations, regions of the country, age groups, and across time. Under additional parametric assumptions, I move from lower bounds to a point estimate that suggest individuals would need to pay markups in excess of 300\% in order to start an insurance market.

Next, I estimate individuals’ willingness to pay for additional UI. There is a large literature documenting the impact of unemployment on yearly consumption growth and scaling by a coefficient of relative risk aversion to estimate an implied willingness to pay for UI. Unfortunately, if individuals know about their future unemployment prospects in the year prior, they may adjust their consumption in response to the realization of that information. In this case, the impact of unemployment on consumption growth will understate the causal effect of unemployment on consumption, and thus understate the value of UI.

I develop a 2-sample IV strategy that inflates the estimated impact on consumption growth by the amount of information revealed in the 1 year before the unemployment measurement.\textsuperscript{5}

\textsuperscript{5}This generalizes the no-trade condition of Hendren (2013b) to allow for moral hazard. This pooled cost depends on the distribution of job loss probabilities but does not depend on the responsiveness of unemployment to UI benefits. The first dollar of insurance provide first-order welfare gains, whereas the behavioral response imposes a second order impact on the cost of insurance, a point recognized by Shavell (1979). So although the behavioral response to insurance is useful for characterizing optimal social insurance, it does not readily provide insight into why a private market does not exist.
I estimate the evolution of beliefs prior to unemployment (measured in the HRS) and the impact of unemployment on food expenditure in the Panel Study of Income Dynamics (PSID).\textsuperscript{6} Unemployment leads to roughly 6-10\% lower consumption growth. Concurrently, roughly 20\% of the information about future unemployment is revealed at the point of 1-year prior to the unemployment measurement. Scaling by $\frac{1}{0.8} = 1.25$ yields an estimate of the causal effect of unemployment on consumption. Assuming a coefficient of relative risk aversion of 2, this suggests individuals are willing to pay no more than a 20\% markup for unemployment insurance; a range of robustness tests all yield estimates below 50\%, well below the 300\% markups individuals would have to be willing to pay to overcome the presence of private information. Private information provides a micro-foundation for why companies do not sell private UI policies.

While the impact of unemployment on consumption characterizes the willingness to pay for UI conditional on one’s beliefs about future unemployment, it does not characterize the social willingness to pay. When people learn ex-ante about future unemployment, UI insures not only against the realization of unemployment, but also against the risk of future unemployment. This latter value of UI is not captured in previous literature, which has focused on the impact of the realization of unemployment conditional on their risk of unemployment.

I provide two methods for identifying the value of insurance against the ex-ante realization of knowledge about future unemployment. First, I extend the two-sample IV strategy used to estimate the causal effect of unemployment on consumption to estimate the causal effect of knowledge about future unemployment on consumption. Using the PSID, I show that in response to unemployment in period $t$, consumption drops by 2.5\% in year $t − 1$ relative to $t − 2$, even amongst those who remain employed in both previous years. Using the HRS, I show that the impact of unemployment in period $t$ increases the beliefs about future unemployment by 10pp in year $t − 1$ relative to year $t − 2$. Scaling the 2.5\% consumption drop by the amount of information revealed in year $t − 1$ relative to $t − 2$ (10\%) suggests fully learning about unemployment leads to a 25\% ex-ante consumption drop prior to becoming unemployed.\textsuperscript{7} Scaling by a coefficient of relative risk aversion of 2, this approach suggests individuals are ex-ante willing to pay at least a 50\% markup for unemployment insurance.

Second, I show that in response to learning about future job loss, spouses are more likely to

\textsuperscript{6}The latter largely replicates existing work (Gruber (1997); Stephens (2001); Chetty and Szeidl (2007))

\textsuperscript{7}Note this response is measured within the set of employed individuals, and hence is less likely to suffer bias from state-dependent utility or the fact that individuals may have more time for home production when unemployed.
enter the labor market. A 10pp increase in the probability of becoming unemployed in the next year increases spousal labor supply by 2.5-3%.

Normatively, one can compare these responses to an extensive margin spousal labor supply semi-elasticity to derive the ex-ante markup individuals would be willing to pay for UI. A semi-elasticity of 0.5 (Kleven et al. (2009)) suggests individuals would be willing to pay a 60% markup to obtain insurance against learning one would become unemployed.

The socially optimal UI benefit level equates a weighted average of the ex-ante and ex-post willingnesses to pay for UI to the aggregate fiscal externality. The results suggest the ex-ante willingness to pay for UI (based on ex-ante responses) exceeds the ex-post willingness to pay based on the consumption impact of unemployment. This suggests previous literature has understated the social value of UI by ignoring its value in providing insurance against the realization of information about future unemployment.

**Related literature** This paper is related to a growing strand of literature studying the degree to which individuals are insured against unemployment and income shocks, and the positive and normative impact of government policy responses. The methods of this paper related to a broad literature using subjective expectation data to identify properties of individual beliefs (Pistaferri (2001); Manski (2004)). Most closely, this paper is related to the work of Stephens (2004) who illustrates that subjective probability elicitions in the HRS are predictive about future unemployment status.

In contrast to many previous approaches, the approaches developed here build upon Hendren (2013b) by estimating theoretically-motivated properties of beliefs while simultaneously allowing the elicitations to be noisy and potentially biased measures of true beliefs. At no point do I assume individuals report their true beliefs on surveys. Rather, I exploit the joint distribution of the elicitations and the corresponding event to infer properties of the distribution of beliefs desired for the positive and normative analysis.

The paper is also related to the large literature documenting precautionary responses to knowledge and uncertainty about future adverse events. To be sure, this paper is not the first to identify the impact of unemployment on consumption, or even the ex-ante response of con-

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8This relates to existing literature documenting the “added worker” effect of spousal unemployment, but suggests part of the spousal response occurs before the onset of unemployment.

9In the UI context, see Baily (1976); Acemoglu and Shimer (1999, 2000); Chetty (2006); Shimer and Werning (2007); Blundell et al. (2008); Chetty (2008); Shimer and Werning (2008); Landais et al. (2010).
consumption or spousal labor supply to future income or unemployment shocks. The contribution of this paper is to provide straightforward methods that combine information on behavioral responses (e.g. consumption and spousal labor supply) and subjective beliefs to both (a) recover the causal effect of both the risk and realization of unemployment on consumption and (b) use these estimates to value social insurance.

This paper also contributes to the growing literature documenting the impact of private information on the workings of insurance markets and the micro-foundations for under-insurance. A primary method for testing for private information is to identify whether insurance contracts are adversely selected (Chiappori and Salanié (2000); Finkelstein and Poterba (2004)). My results suggest this literature has perhaps suffered from a “lamp-post” problem, as suggested by Einav et al. (2010): If private information prevents the existence of entire markets, it is difficult to identify its impact by looking for the adverse selection of existing contracts. Conversely, incorporating subjective expectation information (as in Pistaferri (2001); Manski (2004); Hendren (2013b)) not only helps distinguish the barriers to insurance but can also be used to help quantify the value of social insurance.

The rest of this paper proceeds as follows. Section 2 outlines the theoretical model and derives the estimands that characterize the frictions imposed by private information. Section 3 describes the data. Section 4 estimates the frictions imposed by private information. Section 5 estimates the willingness to pay for UI. Section 6 presents a modified Baily-Chetty formula characterizing the optimal level of government benefits and identifies methods for valuation of UI using ex-ante behavioral responses. Sections 7 and 8 provide estimates of the behavioral responses to information about unemployment on consumption and spousal labor supply, and quantify these impacts on the value of social insurance. Section 9 combines the ex-ante and ex-post valuations into a measure of the social value of additional UI which can be compared to its fiscal cost. Section 10 concludes.

10For example, Barceló and Villanueva (2010); Bloemen and Stancanelli (2005); Carroll et al. (2003); Carroll and Sanwick (1998, 1997); Dynan (1993); Engen and Gruber (2001); Guariglia and Kim (2004); Guiso et al. (1992); Hubbard et al. (1994); Lusardi (1997, 1998), and most closely Stephens (2001); Stephens Jr (2002) for evidence in the PSID.

11Alternative approaches to identifying under-insurance studies the joint distribution of consumption and income (e.g. Meghir and Pistaferri (2011) and Kinnan et al. (2011)). In this sense the paper is related to Pistaferri (2001) by incorporating additional information in subjective probability elicitations to distinguish between barriers to consumption smoothing.
2 Theory

Individuals may have knowledge about their future unemployment prospects and also may respond to the provision of insurance. I develop a theoretical model of unemployment risk capturing these features. In this section, I use the model to derive the estimands characterizing when a private market can exist. In Section 6, I use the same model to characterize the ex-ante (utilitarian) optimal level of social insurance.

2.1 Setup

There exists a unit mass of currently employed individuals indexed by an unobservable type \( \theta \in \Theta \). While \( \theta \) is unobserved, individuals have observable characteristics, \( X \), that insurers could use to price insurance contracts. Individuals may lose their job, which occurs with probability \( p \) that is potentially affected by the individual’s behavior. Individuals choose consumption in the event of being employed, consumption in the event of being unemployed, the probability of losing their job, \( p \), and a set of other actions, \( a \), that can include future consumption, labor effort, and spousal labor supply. Choices are made subject to a choice set \( \{c_e, c_u, p, a\} \in \Omega(\theta) \) that may vary across types and be shaped by existing forms of formal and informal insurance.

Consider an insurance policy that pays \( b \) in the event of being unemployed at a premium of \( \tau \) paid in the event of being employed. The aggregate utility of an insurance policy \((b, \tau)\) is given by

\[
U(\tau, b; \theta) = \max_{\{c_e, c_u, p, a\} \in \Omega(\theta)} (1 - p) u(c_e - \tau) + pu(c_u + b) - \Psi(1 - p, a; \theta) \tag{1}
\]

where \( u(c) \) is the utility over consumption in the state of unemployment, \( v(c) \) is the utility over consumption in the state of employment.\(^{12}\)

There are two key frictions to obtaining full insurance in the model. First, individuals have private information about their types, \( \theta \), and in particular their probability of becoming unemployed, \( p(\theta) \). This creates a potential adverse selection problem. Second, individuals are able to potentially choose their probability of becoming unemployed, which affects the cost of insurance. Hence, there is also a potential moral hazard problem.\(^{13}\) The next section characterizes when a private market can profitably provide some insurance.

\(^{12}\)For notational simplicity, I assume consumption is given by \( c_e - \tau \) if employed and \( c_u + b \) if unemployed so that \( c_u \) and \( c_e \) are consumption choices prior to the UI payments/receipts. Individuals choose \( c_e \) and \( c_u \) after knowing \( b \) and \( \tau \), so that one could equivalently think of the individual as choosing consumption.

\(^{13}\)To see this, consider the case when \( \Psi(1 - p, a; \theta) \) is convex in \( 1 - p \) so that the choice of \( p \) by type \( \theta \) satisfies
2.2 A No Trade Condition

When can a private market profitably sell a private insurance policy, \((b, \tau)\)? 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 \(X\).

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

\[
dU = -(1 - p(\theta)) v(c_e(\theta)) d\tau + p(\theta) u'(c_u(\theta)) db
\]

which will be positive if and only if

\[
\frac{p(\theta) u'(c_u(\theta))}{(1 - p(\theta)) v'(c_e(\theta))} \geq \frac{d\tau}{db}
\]

The LHS of equation (2) is a type \(\theta\)'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. The RHS of equation (2), \(\frac{d\tau}{db}\), is the cost per dollar of benefits of the hypothetical policy.

Let \(\Theta(\frac{d\tau}{db})\) denote the set of all individuals, \(\theta\), who prefer to purchase the additional insurance at price \(\frac{d\tau}{db}\) (i.e. those satisfying equation (2)) who have observable characteristics \(X\). An insurer’s profit from a type \(\theta\) is given by \((1 - p(\theta)) \tau - p(\theta) b\). Hence, the insurer’s marginal profit from trying to sell a policy with price \(\frac{d\tau}{db}\) is given by

\[
d\Pi = E_{\theta \in \Theta(\frac{d\tau}{db})} \left[ (1 - p(\theta)) \tau - p(\theta) b \right] - E_{\theta \in \Theta(\frac{d\tau}{db})} \left[ p(\theta) \right] (\tau + b)
\]

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 offering additional insurance on the cost of providing the baseline amount of insurance. Additional insurance may increase the cost through increased probability of unemployment, \(dE[p(\theta)] > 0\). 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), the first order condition:

\[
v(c_e(\theta) - \tau) - u(c_u(\theta) + b) = \Psi'(1 - p(\theta), a(\theta) ; \theta)
\]

where \(\Psi'(1 - p, a(\theta) ; \theta)\) denotes the first derivative of \(\Psi\) with respect to \(1 - p\), evaluated at the individual’s optimal allocation. Intuitively, the marginal cost of effort to avoid unemployment is equated to the benefit, given by the difference in utilities between employment and unemployment. Note that different types, \(\theta\), may have different underlying probabilities, \(p(\theta)\), that satisfy equation the first order condition.

\[14\)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.

\[15\)To incorporate observable characteristics, one should think of the expectations as drawing from the distribution of \(\theta\) conditional on a particular observable characteristic, \(X\).
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

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

(3)

If inequality (3) 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).

To this point, the model allows for an arbitrary dimensionality of unobserved heterogeneity, $\theta$. 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 simplification of the unobserved heterogeneity.

Assumption 1. (Uni-dimensional Heterogeneity). Assume the mapping $\theta \rightarrow p(\theta)$ is 1-1 and invertible and continuously differentiable in $b$ and $\tau$. Moreover, the marginal rate of substitution,

$$\frac{p}{1-p} \frac{u'(c_u(p))}{v'(c_e(p))},$$

is increasing in $p$.

Assumption 1 states that the underlying heterogeneity can be summarized by one’s belief, $p(\theta)$. 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 $p(\theta)$ is indifferent will be the set of higher risks whose probabilities exceed $p(\theta)$. Let $P$ denote the random variable corresponding to the distribution of probabilities chosen in the population in the status quo world without a private unemployment insurance market, $b = \tau = 0$. 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 1, equation (3) can be re-written as:

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

(4)

where $T(p)$ is given by

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

which is the pooled cost of worse risks, termed the “pooled price ratio” in Hendren (2013b). 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.

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

For simplicity, the remainder of the paper will operate under the simplification offered by Assumption 1. However, it is important to note that the results do extend to multi-dimensional heterogeneity. In the case when there are two types $\theta$ with different willingnesses to pay but the same probability of unemployment, types do not map 1-1 into $p(\theta)$, and equation (3) does not summarize the no trade condition. However, Appendix A.1 shows that there exists a mapping, $f(p)$, from a subset of $[0,1]$ into the type space, $\Theta$, such that the no trade condition reduces to testing

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

(5)

Hence, the pooled price ratio continues to be a key measure for the frictions imposed by private information even in the presence of multi-dimensional heterogeneity.\(^{17}\)

**Minimum and average** $T(p)$ What statistics of $T(p)$ are desired for estimation? The no trade condition in equation (4) must hold for all $p$. Absent particular knowledge of how the willingness to pay for UI varies across $p$, it is natural to estimate the minimum pooled price ratio, $\inf T(p)$, as in Hendren (2013b). If no one is willing to pay this minimum pooled price ratio, then the market cannot exist.\(^{18}\)

But, by taking the minimum one implicitly assumes that an insurer trying to start up a market would be able to a priori identify the best possible price that would minimize the markup imposed by adverse selection. In contrast, if insurers do not know exactly how best to price the

\(^{17}\)Appendix A further discusses the generality of the no trade condition. 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. Hendren (2013b) considers this more general case with menus in a model without moral hazard and shows that when the no trade condition holds, pooling delivers weakly higher profit than a separating contract. In Appendix A.2, I show that a version of the present model without the multi-dimensional heterogeneity can be nested into that model.

\(^{18}\)Although not a necessary condition, the no trade condition will hold if

\[ \sup_{p \in [0,1]} \frac{u'(c_u(f(p)))}{u'(c_e(f(p)))} \leq \inf_{p \in [0,1]} T(p) \]

so that absent particular knowledge about how the willingness to pay varies across $p$, the minimum pooled price ratio provides guidance into the frictions imposed by private information.
insurance (e.g., because there is no market from which to learn the distribution of types), the
price of adverse selection imposed on a potential market entrant could be higher and depend
on other properties of the pooled price ratio. This can motivate the average pooled price ratio,
\( E[T(p)] \), as a complementary statistic for studying the degree of potential adverse selection.

To see this, 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. Let’s say this person has a probability \( p \) of becoming
unemployed and for simplicity assume the mapping from types to \( p \) is one-to-one. 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. Then the insurer
tries to sell this policy to the marketplace; clearly, all risks \( P \geq p \) will choose to purchase the
policy as well. Therefore, 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

\[
    E\left[ \frac{u'(c_u(p))}{v'(c_e(p))} \right] \geq E[T(P)] \tag{6}
\]

If the insurer is randomly choosing contracts to try to sell, it is not the minimum pooled price
ratio that determines profitability. Rather, on average, individuals would have to be willing
to pay the pooled price ratio, \( E[T(P)] \). In this sense, the average pooled price ratio provides
guidance on the frictions imposed on a potential insurance company entrant that would attempt
to set up a market through experimentation. From a more practical standpoint, Section 4
will illustrate that one can construct lower bounds on \( E[T(p)] \) under weaker assumptions than
are required to estimate the minimum pooled price ratio. Hence, it will be useful to have in
mind the theoretical relationship between \( E[T(p)] \) and the barriers to trade imposed by private
information.

3 Data

The analysis primarily draws upon data from the Health and Retirement Study (HRS). The
analysis of food expenditure responses to unemployment will use the Panel Study of Income
Dynamics (PSID).
3.1 HRS

I use data from all available waves of the Health and Retirement Study (HRS) spanning years 1992-2013. The HRS samples individuals generally over 55 and their spouses (included regardless of age). Table I presents the summary statistics for the main variables and samples used in the analysis.

**Subjective probability elicitations** The survey asks respondents: what is the percent chance (0-100) that you will lose your job in the next 12 months? I denote these free-responses by $Z$. Figure I presents the histogram of the subjective probability elicitations. As has been noted in previous literature (Gan et al. (2005)), these responses tend to concentrate on focal point values, especially zero. Taken literally, a response of zero or 100 implies an infinite willingness to pay for certain financial contracts, which clearly contrasts with both common sense and observed behavior. As a result, at no point in the present paper are these elicitations used as true measures of individuals beliefs (i.e. $Z \neq P$). Instead, I build on the approach of Hendren (2013b) which uses these elicitations as noisy and potentially biased measures of true beliefs to identify and quantify private information, as illustrated in Section 4.

**Incidence of Job Loss** Corresponding to the elicitation, the survey allows for the construction of whether or not the individual will involuntarily lose their job in the subsequent 12 months from the survey, denoted $U$. The subsequent wave asks individuals whether they are working at the same job as the previous wave (roughly 2 years prior). If not, respondents are asked when and why they left their job (e.g. left involuntarily, voluntarily/quit, or retired). To most closely align with the wording of the subjective probability elicitation, I define becoming unemployed as involuntarily losing one’s job in the subsequent 12 months following the previous survey date, and I exclude voluntary quits and retirement in the baseline specifications. As a result, the empirical work will estimate the frictions imposed by private information on a hypothetical insurance market that pays $1 in the event the individual involuntarily loses his/her job in the subsequent 12 months.

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19 The most recent available core wave is 2012; Appendix C utilizes data from the 2013 consumption (CAMS) module in the HRS.

20 Despite its focus on an older set of cohorts, the HRS is a natural dataset choice because it contains information on unemployment, consumption, a wide range of observable characteristics insurers use in other markets to price policies, and, most importantly, subjective probability elicitations about future unemployment.
I also consider robustness analyses to other definitions of job loss. I construct a measure of job loss in the 6-12 months following the survey. This removes cases where the individuals knew about an immediately impending job loss that could potentially be circumvented by an insurer imposing a waiting period on the insurance policy. I also construct measures of job loss in the 6-24 month window, and measures of whether the individual is unemployed in the subsequent survey round (roughly 24 months after the previous survey).\textsuperscript{21}

**Public Information** Estimating private information requires specifying the set of observable information insurers could use to price insurance policies. The data contain a very rich set of observable characteristics that well-approximate variables used by insurance companies in disability, long-term care, and life insurance (Finkelstein and McGarry (2006); He (2009); Hendren (2013b)) and also contain a variety of variables well-suited for controlling for the observable risk of job loss. The baseline specification includes a set of these job characteristics including job industry categories, job occupation categories, log wage, log wage squared, job tenure, and job tenure squared, along with a set of demographic characteristics (census division dummies, gender dummies, age, age squared, and year dummies).\textsuperscript{22}

I also assess robustness to additional health status controls that include indicators for a range of doctor-diagnosed medical conditions (diabetes, a doctor-diagnosed psychological condition, heart attack, stroke, lung disease, cancer, high blood pressure, and arthritis) and linear controls for bmi.\textsuperscript{23} I also consider specifications that condition on lagged unemployment incidence, and also to a less comprehensive set of controls such as just age and gender. Changing the set of observable characteristics simulates how the potential for adverse selection varies with the underwriting strategy of the potential insurer.

\textsuperscript{21}In addition, there is a difference between job loss and unemployment, as some who lose their job may quickly find another job and have less need for unemployment insurance. To identify the frictions facing a private unemployment insurance market, which may differ from a “job loss” insurance market, I construct measures of job loss that are the product of these indicators with an indicator for receiving positive government unemployment insurance benefits in between survey waves, thereby restricting to the set of job losses that led to a government UI claim. This will simulate the frictions faced for an insurance policy that provides an additional dollar of government UI benefits.

\textsuperscript{22}This set is generally larger than the set of information previously used by insurance companies who have tried to sell unemployment insurance. Income Assure, the latest attempt to provide private unemployment benefits, prices policies using a coarse industry classification, geographical location (state of residence), and wages.

\textsuperscript{23}As shown in Panel 2 of Table 1, 22,831 observations of the 26,640 baseline observations report non-missing values for these health variables.
Samples  I begin with a sample of everyone under 65 currently holding a job who is asked the subjective probability elicitation question, $Z$. I keep only those respondents who have non-missing job loss responses in the subsequent wave, $U$, and those with non-missing observable characteristics, $X$. I exclude the self-employed and those employed in the military.

Table I presents the summary statistics of the samples used in the paper. There are 26,640 observations in the sample, which correspond to 3,467 unique households. The average age is 56 and roughly 40% of the sample is male. Mean yearly wages are around $36,000 in the baseline sample and average job tenure is 12.7 years.

In the subsequent 12 months from the survey, 3.1% of the sample reports losing their job involuntarily. In contrast, the mean subjective probability elicitation is 15.7%. This indicates a significant bias in elicitation on average. This is arguably a well-known artifact of the non-classical measurement error process inherent in subjective elicitation. Elicitations are naturally bounded between 0 and 1. Hence, for low probability events, there is a natural tendency for measurement error in elicitation to lead to an upward bias in elicitation. This provides further rationale for treating these elicitation as noisy and potentially biased measures of true beliefs, as is maintained throughout the empirical analyses below.

3.2 PSID

To explore the willingness to pay for UI, I analyze the impact of unemployment on consumption. While the HRS provides subjective probability elicitation, it does not provide high quality data on consumption patterns. As a result, many papers studying optimal unemployment insurance have used the PSID to measure the impact of unemployment on consumption (Gruber (1997); Chetty and Szeidl (2007)). Following these, I utilize the PSID sample containing data on food expenditure for years spanning 1971-1997. I restrict the sample to heads of household between the ages of 25 and 65 who have non-missing food expenditure and employment status variables. I define food expenditure as the sum of food expenditure in the home and out of the home, plus food stamps. Following Gruber (1997), I restrict the baseline sample to those with less than

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$^{24}$ Although the HRS focuses on an older population, I present evidence below that the patterns are quite stable across the age ranges observed in the data.

$^{25}$ To compute food stamp expenditure, I follow previous literature and use the response to the monthly food stamp amount multiplied by 12. Results for the impact on consumption in $t-2$ relative to $t-1$ are robust to alternative measures of food stamps, such as using the annual measures. However, the size of the consumption drop upon unemployment is larger when using the annual food stamp expenditure question instead of the monthly response multiplied by 12.
a threefold change in food expenditure relative to the previous year. I define an indicator for
unemployment at the time of the survey that exclude temporary layoffs. I also utilize a measure
of household expenditure needs, which the PSID constructs to measure the total expenditure
needs given the age and composition of the household.

Appendix Table III provides the summary statistics for the sample. The PSID sample
provides more than 11,000 household-head observations with food consumption data in the
primary sample. The mean age is 40 and the respondents are 80% male. For comparison to
the HRS sample, I also present results for older sub-samples. Roughly 5.9% of the sample is
unemployed at the time of the survey, and the average nominal consumption growth is 0.049.
All analysis below will use log specifications with year dummies, so I do not adjust for inflation.

4 Empirical Evidence of Private Information

4.1 Presence of Private Information and Lower Bounds on $E[T(P)]$

Do people have private information about their likelihood of becoming unemployed? I begin
by asking whether the subjective probability elicitations, $Z$, are predictive of subsequent un-
employment, $U$, conditional on observable demographic and job characteristics, $X$. Figure II
(Panel A) bins the elicitations into 5 groups and presents the coefficients on these indicators in
a regression of $U$ on these bin dummies and the observable controls, $X$. The figure displays a
clear increasing pattern: those with higher subjective probability elicitations are more likely to
lose their job, conditional on demographics and job characteristics.

While Figure II (Panel A) presents evidence that individuals have knowledge about their
future unemployment prospects, it does not quantify the frictions imposed by private information
on the workings of an insurance market. For this, I proceed in several steps. First, consider the
predicted values

$$P_Z = \Pr\{U|X, Z\}$$

Under a couple of natural assumptions, Hendren (2013b) shows that the distribution of predicted
values, $P_Z$, forms a distributional lower bound on the distribution of true beliefs, $P$.

Remark 1. (Hendren (2013b)) Suppose (a) elicitations contain no more information about $U$
than does $P$: $\Pr\{U|X, Z, P\} = \Pr\{U|X, P\}$ and (b) true beliefs are unbiased $\Pr\{U|X, P\} = P$.  

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Then true beliefs are a mean-preserving spread of the distribution of predicted values:

\[ E[P|X,Z] = P_Z \]

Under these minimal assumptions about the nature of how elicitations relate to beliefs, the distribution of true beliefs, \( P \), is more dispersed than the observed distribution of predicted values, \( P_Z \).

Figure II, Panel B constructs the distribution of the predicted values of \( P_Z - \Pr\{U|X\} \).26 If individuals had no private information, this distribution would be statistically identical to a point mass at 0. Instead, the figure reveals a significant upper tail of predicted probabilities lying above the mass of low-risks. The logic of adverse selection suggests that in order to start a profitable insurance market, the mass of low-risks would need to be willing to pay a large enough markup to cover the costs of these higher risks.

To make this logic precise, one can use the distribution of \( P_Z \) to generate a lower bound on \( E[T(P)] \). Consider a particular observable characteristic, \( X = x \) and define \( m(p) = E[P - p|P \geq p] \) to be the mean residual life function of the distribution \( P \) for those with \( X = x \). Intuitively, \( m(p) \) asks “how much worse are the worse risks than \( p \)?” Note that \( m(p) \) is not observed without observing the true distribution of \( P \). But, one can construct a sample analogue of \( m(p) \) using the distribution of predicted values, \( P_Z \):

\[ m_Z(p) = E[P_Z - p|P_Z \geq p] \]

Proposition 1 shows that the average mean residual life of \( P_Z \), normalized by the mean probability of unemployment in the population, yields a lower bound on the average pooled price ratio, \( E[T(P)] \).

**Proposition 1.** Suppose (a) elicitations contain no more information about \( U \) than does \( P \): \( \Pr\{U|X,Z,P\} = \Pr\{U|X,P\} \) and (b) true beliefs are unbiased \( \Pr\{U|X,P\} = P \). Then,

\[ E[T(P)] - 1 \geq E[T_Z(P_Z)] - 1 \]  

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26 To construct this figure, I use a probit specification in \( X \) and \( Z \) that includes a second order polynomial in \( Z \) to capture the potential nonlinearities, such as the moderately convex relationship illustrated in Figure II, and also indicators for \( Z = 0, Z = 0.5, \) and \( Z = 1 \) to capture focal point responses illustrated in Figure I. This produces the predicted values, \( P_Z \). To construct \( \Pr\{U|X\} \), I run the same specification but exclude the \( Z \) variables. Results are similar using a linear specification (as shown in Appendix Table I), but since the mean probability of becoming unemployed is very close to zero (3.1%) the probit specification has a better fit since the specification is not fully saturated in \( X \) and \( Z \).
where

\[ T_Z(P_Z) = 1 + \frac{m(P_Z)}{\Pr\{U\}} \]

Proof. (See Appendix B) The proof extends results in Hendren (2013b) by applying Jensen’s
inequality to \( T(P) \).

The extent to which the average pooled price ratio, \( E[T(p)] \), exceeds 1 is bounded below by

\[ E[m(Z(P_Z))] / Pr\{U\} \]

Intuitively, \( E[m(Z(P_Z))] \) provides a lower bound on the average extent to
which risks have higher probabilities than \( p \), so that the ratio relative to the mean probability,
\( Pr\{U\} \), provides a lower bound on the average markup over actuarially fair prices that one
would have to pay to cover the cost of the higher risks.

Table II presents the results.\(^{27}\) For the baseline specification with demographic and job
characteristic controls, the average markup imposed by the presence of worse risks is at least
76.82% (s.e. 5.3%), suggesting \( E[T(P)] \) \( \geq \) 1.7682. Adding health controls changes this slightly
to 71.98% (s.e. 5.2%); dropping the job characteristic controls increases this slightly to 80.33%
(s.e. 5.1%). The presence of such markups impose significant barriers to the existence of a
private insurance market for UI.

Figure III presents estimates of the markups for a range of specifications. Panel A considers
specifications with alternative control variables (\( X \)), plotting estimates of \( E[T_Z(P_Z)] \) against
the pseudo-R squared of the model for \( Pr\{U|X,Z\} \). Including job characteristics significantly
increases the predictive power of the model, but it does not meaningfully reduce the barrier
to trade imposed by private information relative to specifications with only demographic con-
trols. Intuitively, the additional job characteristics controls help better predict unemployment
entry rates across industry and occupation groups; but it does not remove the thick upper tail
illustrated in Figure II, Panel B.\(^{28}\)

\(^{27}\)As in Hendren (2013b), the construction of \( E[T_Z(P_Z)] \) and \( E[m_Z(P_Z)] \) is all performed by conditioning on
\( X \). To partial out the predictive content in the observable characteristics, I first construct the distribution of
residuals, \( P_Z - Pr\{U|X\} \). I then construct \( m_Z(p) \) for each value of \( X \) as the average value of \( P_Z - Pr\{U|X\} \)
above \( p + Pr\{U|X\} \) for those with observable characteristics \( X \). In principle, one could estimate this separately
for each \( X \); but this would require observing a rich set of observations with different values of \( Z \) for that given \( X \).
In practice, I follow Hendren (2013b) and specify a partition of the space of observables, \( \zeta_j \), for which I assume
the distribution of \( P_Z - Pr\{U|X\} \) is the same for all \( X \in \zeta_j \). This allows the mean of \( P_Z \) to vary richly with \( X \),
but allows a more precise estimate of the shape by aggregating across values of \( X \) and \( \zeta_j \). In principle, one could
choose the finest partition, \( \zeta_j = \{X_j\} \) for all possible values of \( X = X_j \). However, there is insufficient statistical
power to identify the entire distribution of \( P_Z \) at each specific value of \( X \). For the baseline specification, I use an
aggregation partition of 5 year age bins by gender. Appendix Table I (Columns (3)-(5)) documents the robustness
of the results to alternative aggregation partitions.

\(^{28}\)Appendix Table I explores robustness to various specifications, including linear versus probit error structures,
Adding further controls does not appear to significantly modify the frictions imposed by private information, nor does it significantly alter the R-squared of the model. Controlling for health information does not meaningfully change the estimates, nor does adding additional controls for their work history such as controls for indicators for being employed in the previous two survey waves, as indicated by the “Demo, Job, History” specification. Conversely, dropping the demographic variables such as region, year, gender etc and solely using age and age squared leads to a similar magnitude of private information relative to the baseline specification. Intuitively, the friction imposed by private information is driven by the thick upper tail of personally-specific knowledge that an individual may have that he or she has a particular chance at losing his or her job.

To illustrate the difficulty faced by a potential insurer in removing the information asymmetry, Figure III, Panel B adds individual fixed effects to a linear specification for \( \Pr\{U|X,Z\} \).\(^{29}\) Of course, such fixed effects would be impossible for an insurer to use – an econometrician can view the fixed effects as nuisance parameters that drop out in a linear fixed effects model; in contrast, an insurer must view them as a key input into their pricing policy.\(^{30}\) This dramatically increases the R-squared of the model, but the residuals suggest individuals would still on average have to be willing to pay at least a 40% markup to cover the pooled cost of worse risks.\(^{31}\) In short, the information asymmetry is robust across a wide set of control specifications.

**Population Heterogeneity** Columns (4)-(9) of Table II and Figure III (Panels C-F) explore how the estimated markups vary across subsamples. There is substantial amounts of private information across all industries (Panel C) and occupations (Panel D), with lower bounds on \( E[T(P)] - 1 \) all exceed 50%. The presence of significant amounts of private information about future job loss also spans the age spectrum in the data (45-65), as shown in Columns (4)-(5).\(^{32}\)

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29 I use the linear specification so that the residuals, \( P_Z - \Pr\{U|X\} \) are well identified and do not suffer bias from the inability to consistently estimate the nuisance parameters. Appendix Table I, Column (2) illustrates that the baseline value for \( E[T_Z(P_Z)] - 1 \) is 0.6802 (s.e. 0.051) when using the linear specification for \( \Pr\{U|X,Z\} \) as opposed to the baseline value of 0.7687 using the probit specification. Hence, a small amount of the attenuation illustrated in Figure III, Panel B (where the fixed effects specification yields 0.40) for the fixed effects estimates relative to the baseline is driven by the specification change from probit to linear.

30 Moreover, the econometrician is able to construct these fixed effects ex-post (after observing \( U \) realizations for the individual over many years), whereas an insurer would generally attempt to construct this ex-ante.

31 Relatedly, while the autocorrelation in \( Z \) across waves is around 0.25, there exists significant predictive content within person, which is consistent with the individual’s elicitation containing largely personal and time-varying knowledge about future job loss.
of Table III and Panel E of Figure III. The estimates are also similar across below- and above-
median wage workers, with lower bounds of 65% and 95%, as shown in Columns (6)-(7) of Table
II. Appendix Figure I also shows the results are similar across all years (Panel A) and across all
census divisions in the U.S. (Panel B).

One underwriting strategy that has been common in other insurance markets is to limit the
insurance market to “good risks”. Figure III, Panel F asks whether a similar underwriting
strategy could help open up an unemployment insurance market for those with a low chance of
losing their job. The figure plots the estimated $E[T_{Z}(P_{Z})] − 1$ for subsamples with high job
tenure and steady work histories. In contrast to the idea that restricting to good risks would
help open up an insurance market, the figures illustrate if anything the opposite pattern: better
risk populations have higher markups. Indeed, for those with greater than 5 years of job tenure,
the data suggest a lower bound of 110% despite having a less than 2% chance of losing their job
in the subsequent 12 months.

Loosely, the data is consistent with there always being at least one bad apple in every
bunch that knows s/he has a decent chance of losing his/her job. This presents an especially
high burden on a sample that have very low probabilities of unemployment, leading to higher
implicit markups for these groups and preventing insurers from opening up markets to those
who, based on observables, seem like especially good risks.

**Alternative outcomes and waiting periods** The results suggest high markups imposed by
private information on a hypothetical insurance market that pays $1 in the event of becoming
unemployed in the subsequent 12 months. One alternative market – which would be consistent
with insurance policies in other contexts – would be to impose waiting periods of, for example, 6
months before the insurance goes into effect. Indeed, if the private information is primarily about
knowing that one will lose their job next week, then excluding next week from the insurance
contract payouts could remove the informational asymmetry.

Appendix Table I considers an alternative definition of $U$ that excludes those who become

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32 For example, health-related insurance markets generally exclude those with pre-existing conditions. Hendren
(2013b) shows this is consistent with those risks having private information but healthy individuals not. Loosely,
those results suggest that there’s one way to be healthy, but many unobservable ways to be sick. This pattern
prevents the existence of insurance markets for those with pre-existing conditions, but the ability of insurers to
limit such risks from risk pools allows for insurance markets for the healthy that are less afflicted by problems of
private information.
unemployed in the first 6 months after the survey. This yields a lower bound of 57.9% ($p < 0.001$) for a market that imposes a 6-month waiting period. The frictions imposed by private information cannot be removed through the imposition of waiting periods.

Another strategy could be to require individuals to also file for unemployment insurance with the government. Such a practice could impose higher take-up hurdles and also help mitigate claims from job loss events that don't lead to significant periods of unemployment. To assess the potential barriers to trade imposed by private information in such a market, I construct an outcome that is the interaction of unemployment with whether or not the individual receives government UI benefits. Appendix Figure I, Panel C plots the estimated lower bounds, $E[T(P)] - 1$, for such a hypothetical market. Restricting to government UI for a 0-12 month contract has a lower bound on the average markup of roughly 95%. The markups remain high for other potential timelines, such as 0-24 and 6-24 month payout windows. Restricting insurance payouts to cases in which the individuals filed government UI benefits would not appear to significantly reduce the barriers to trade imposed by private information.

Overall, the results document significant lower bounds on the average markups individuals would have to be willing to pay in order to cover the pooled cost of worse risks. They generally exceed 50% across a wide set of specifications, subsamples, and controls for observable characteristics. Moreover, these lower bounds are derived solely using the assumptions outlined in Remark 1 that allow the elicitations to be noisy and potentially biased measures of true beliefs. But, they do not provide estimates of $\inf T(p)$ and they are lower bounds, not point estimates.

The next subsection adds additional assumptions about the nature of the measurement error in the elicitations (the relation between $Z$ and $P$) that allows one to move from a lower bound on $E[T(P)]$ to point estimates for $T(p)$ and its minimum, $\inf T(p)$.

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33 I continue to use the same elicitation, $Z$, in the construction of the distribution of predicted values. This is appropriate because $Z$ can still satisfy the assumptions in Remark 1 for the alternative measure of $U$; but is likely to be a noisier measure of the individual’s true beliefs about losing his or her job in the 6-12 months after the survey, as opposed to the 0-12 months after the survey, as is prompted in the elicitation. Hence, one might expect lower values for $E[T(Z)(PZ)]$ because of this additional measurement error, but it remains a lower bound for the true markup that would be imposed by the presence of private information for an insurance contract that paid $b$ in the event of unemployment with a 6-month waiting period.

34 I also abstract from the ability of an individual to change the timing of their unemployment. Such claim timing could impose additional adverse selection costs. In principle, if such timing responses are costly to the worker, they would be a behavioral response that would not affect the insurer’s costs for the first dollar of insurance when $b = \tau = 0$. But, this could be an additional cost factor with non-marginal contracts, as has been noted in other market contexts such as dental insurance (Cabral (2013)).

34 Indeed, this is part of the strategy taken by the most recent attempt at providing unemployment insurance by Income Assure.
4.2 Point Estimates of $\inf T(p)$

To generate a point estimate for the pooled price ratio and its minimum, one requires an estimate of the distribution of beliefs, $P$. To obtain this, I follow Hendren (2013b) by making additional assumptions about the distribution of measurement error in the elicitions. Note that the observed density (p.d.f./p.m.f.) of $Z$ and $U$ can be written as

$$f_{Z,U}(Z,U|X) = \int_0^1 p^U (1-p)^{1-U} f_{Z|P,X}(Z|P=p,X) f_P(p|X) \, dp$$

where $f_{Z|P,X}$ is the distribution of elicitations given true beliefs (i.e. elicitation error) and $f_P$ is the distribution of true beliefs in the population (which can be used to construct $T(p)$ at each $p$). This is obtained by first taking the conditional expectation with respect to $p$ and then using the assumption that $\Pr\{U|Z,X,P\} = P$.

To estimate the distribution of beliefs, $f_P$, I assume that the distribution of elicitation error, $f_{Z|P}(Z|P)$ can be represented by a low-dimensional vector of parameters; I then estimate these parameters along with a flexible specification for the distribution of true beliefs, $f_P(p|X)$.

I follow Hendren (2013b) by assuming that $Z = P + \epsilon$, where $\epsilon$ has the following structure. With probability $\lambda$, individuals report a noisy measure of their true belief $P$ that is drawn from a $[0,1]$-censored normal distribution with mean $P + \alpha(X)$ and variance $\sigma^2$. With this specification, $\alpha(X)$ reflects potential bias in elicitations and $\sigma$ 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)). To capture these, I assume that with probability $1 - \lambda$ individuals take their noisy report with the same bias $\alpha(X)$ and variance $\sigma^2$, but censor it into a focal point at 0, 50, or 100. If their elicitation would have been below $\kappa$, they report zero. If it would have been between $\kappa$ 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, $Z$.\footnote{Specifically, the p.d.f./p.m.f. of $Z$ given $P$ is given by

$$f(Z|P,X) = \begin{cases} 
(1 - \lambda) \Phi \left( \frac{-P - \alpha(X)}{\sigma} \right) + \lambda \Phi \left( \frac{\kappa - P - \alpha(X)}{\sigma} \right) & \text{if } Z = 0 \\
\lambda \left( \Phi \left( \frac{1 - \kappa - P - \alpha(X)}{\sigma} \right) - \Phi \left( \frac{\kappa - P - \alpha(X)}{\sigma} \right) \right) & \text{if } Z = 0.5 \\
(1 - \lambda) \Phi \left( \frac{1 - P - \alpha(X)}{\sigma} \right) + \lambda \left( 1 - \Phi \left( \frac{1 - \kappa - P - \alpha(X)}{\sigma} \right) \right) & \text{if } Z = 1 \\
\frac{1}{2} \phi \left( \frac{Z - P - \alpha(X)}{\sigma} \right) & \text{if } o.w.
\end{cases}$$

where $\phi$ denotes the standard normal p.d.f. and $\Phi$ the standard normal c.d.f. 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, $Z$.}
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 (2013b) and adopt an index assumption on the cumulative distribution of beliefs,

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

(8)

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 ($F(p|X) = 1 \{p \leq \Pr\{U|X\}\}$). $^{36}$

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 (2013b), 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. $^{37}$ Formally, I assume

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

where $\alpha_i$ are a set of point masses in $[0, 1]$ and $\xi_i$ 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 (2013b), estimation of the minimum $T(p)$ across the full support of the type distribution is not feasible because of an

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$^36$Moreover, it allows the statistical model to easily impose unbiased beliefs, so that $\Pr\{U|X\} = \mathbb{E}[P|X]$ for all $X$.

$^37$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.
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.

**Results** Table III reports the results. I estimate a value of \( \inf T (p) - 1 \) of 3.36 in the baseline specification. This suggests that unless people are willing to pay a 336% (s.e. 20%) markup in order to obtain unemployment insurance, the results are consistent with the absence of a private market. Including health controls reduces this markup slightly to 323% (s.e. 26.8%), and using only demographic controls increases the markup to 530% (s.e. 65.5%).

The results are also quite robust across subsamples, as illustrated in Columns (4)-(9) of Table III. Consistent with the findings in the lower bound analysis, I find larger barriers to trade imposed by private information for those with longer tenure backgrounds (and hence lower unemployment probabilities on average), with values of \( \inf T (p) - 1 \) of 473.6%. The results are similar across age groups (3.325 for ages at or below 55 and 3.442 for ages above 55); and they are slightly higher for below-median wage earners (4.217) than above-median wage earners (3.223). Overall, the results suggest private information imposes a significant barrier to the existence of a private unemployment insurance market.

For comparison, Hendren (2013b) uses the same empirical strategy to study whether private information prevents those with pre-existing conditions from being able to purchase insurance in three market settings: Long-Term Care insurance, Life insurance, and Disability insurance. In those settings, the estimated markups are all below 100%: 42% for Life, 66% for Disability, and 83% for Long-Term Care. Appendix Figure II illustrates this comparison. The size of the barrier to trade imposed by private information about future unemployment risk appears to be quite substantial.

## 5 Private Willingness to Pay

Would individuals be willing to pay these 300%+ markups for UI? There is an extensive literature focused on estimating the markup individuals are willing to pay for additional unemployment insurance by measuring the causal effect of unemployment on consumption growth. But if individuals know about their potential future unemployment, their consumption may respond

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38 Appendix Table II presents the raw point estimates for \( \alpha_i \) and \( \xi_i \). It suggests there is a small (e.g. 10%) sub-sample of the population that has a very high chance of losing their job. The presence of this upper tail drives these high estimated markups.
ex-ante, reducing the estimated impact of unemployment on consumption. This section develops methods to estimate willingness to pay when individuals have such knowledge.

5.1 Theory

Recall this willingness to pay of a type $p$ is given by their marginal rate of substitution, $\frac{u'(c_u(p))}{v'(c_e(p))}$, where $c_u(p)$ and $c_e(p)$ are the consumption of an individual with ex-ante beliefs, $p$, in the event he or she is unemployed or employed. As noted by Baily (1976) and Chetty (2006), this willingness to pay for UI depends on the causal impact of the event of unemployment on marginal utilities of consumption. If utility over consumption is state independent ($v = u$), one can use a Taylor expansion for $u'$ around the consumption when employed, $u'(c) \approx u'(c_e(p)) + u''(c_e(p))(c - c_e(p))$ to yield the approximation:

$$\frac{u'(c_u(p))}{u'(c_e(p))} \approx 1 + \sigma \frac{\Delta c}{c_e(p)}$$

where $\frac{\Delta c}{c_e(p)} = \frac{c_e(p) - c_u(p)}{c_e(p)}$ is the causal effect of the event of unemployment on type $p$’s percentage difference in consumption and $\sigma$ is the coefficient of relative risk aversion, $\sigma = \frac{c_e(p)u''(c_e(p))}{u'(c_e(p))}$. Following previous literature, it is common to approximate this percentage change using log consumption,

$$\frac{\Delta c}{c_e(p)} \approx \log(c_e(p)) - \log(c_u(p))$$

and to construct the average markup individuals would be willing to pay for UI

$$W^{Ex-post} = \sigma E[\log(c_e(p)) - \log(c_u(p))]$$

where the super-script “Ex-post” indicates that this is the willingness to pay for UI conditional on learning $p$.

In principle, one could attempt to estimate $W^{Ex-post}$ using the cross-sectional relationship between consumption and unemployment. But, this may not reveal the causal impact of unemployment on consumption because those that experience more unemployment may have other attributes (e.g. lower wages, assets, unobservable skills, etc.) that cause lower consumption in both employed and unemployed states of the world.

Consumption growth and the Euler equation  To circumvent these identification concerns, existing literature often estimates the impact of unemployment on yearly consumption
first differences (Gruber (1997); Chetty and Szeidl (2007)). But if individuals learn ex-ante about their potential future unemployment, lagged consumption may differ between subsequently employed and unemployed due to this knowledge, as opposed to differences in ex-ante heterogeneity. This suggests that the impact of unemployment on consumption growth may not capture the causal effect of unemployment.

To see this, let \(v(c_{\text{pre}})\) denote the utility from consumption at the time of learning one’s type, \(\theta\) (and hence \(p(\theta)\)), which is assumed to be additively separable in the utility function (note that \(c_{\text{pre}}\) is captured in the model of Section 2 by considering it an element of \(a\)). This yields the Euler equation:

\[
v' (c_{\text{pre}} (p)) = pu' (c_u (p)) + (1 - p) v' (c_e (p)) \tag{10}
\]

so that the marginal utility of consumption today is equated to the expected marginal utility of consumption in the future. Hence, those with higher values of \(p\) will have a tendency to have a higher marginal utility of consumption (and hence lower consumption) than those with lower values of \(p\).

Now, suppose one were to run a regression of the first difference in consumption, \(dlog (c) = \log (c) - \log (c_{\text{pre}})\), on an indicator for unemployment, \(U\). One can expand the estimated coefficient into two terms:

\[
E [dlog (c) | U = 1] - E [dlog (c) | U = 0] = \underbrace{E [\log (c_e) - \log (c_u)] - E [\log (c_{\text{pre}}) | U = 1]}_{\text{Causal Effect}} - \underbrace{(E [\log (c_{\text{pre}}) | U = 0] - E [\log (c_{\text{pre}}) | U = 1])}_{\text{Bias from ex-ante response}}
\]

The first term is the causal effect of unemployment on consumption – the term desired for measuring willingness to pay. The second term is the difference in current consumption in the year prior to the unemployment spell, \(c_{\text{pre}}\), between those who subsequently become unemployed and those who do not. If individuals have no knowledge of future unemployment \(U\), then their consumption today should not reflect whether or not they become unemployed in the future. However, if individuals learn they may become unemployed, then they may choose to smooth their consumption so that unemployment’s impact on consumption growth will understate its total impact on consumption.

An IV Strategy To solve the consumption bias, I develop a two-sample IV strategy to scale the estimated impact of unemployment on 1-year consumption growth by the amount of information realized in the 1-year period.\(^{39}\) The Euler equation suggests that the ex-ante response

\(^{39}\)An alternative strategy would be to use longer lags or a rich set of demographic control variables instead of 1-year lagged consumption. However, to the extent to which these controls do not capture all differences in \(\theta\),
should also be related to the causal effect of unemployment. Appendix D.1 provides conditions under which the bias can be expressed as:

$$\text{BIAS} = (E[P|U = 1] - E[P|U = 0])(E[\log(c_e) - \log(c_u)])$$

In a wide class of models, the ex-ante response to learning that unemployment is 1% more likely is equal to 1% of the difference in consumption under employment and unemployment. In this case, one can recover the average causal effect of unemployment on log consumption:

$$E[\log(c_e(p)) - \log(c_u(p))] = \frac{E[d\log(c)|U = 1] - E[d\log(c)|U = 0]}{1 - (E[P|U = 1] - E[P|U = 0])}$$  \hfill (11)

The average causal effect of unemployment on the causal effect is given by the impact of unemployment on consumption growth, scaled by the amount of information that is revealed over the year prior to the unemployment measurement, $1 - (E[P|U = 1] - E[P|U = 0])$. If individuals have no knowledge about future unemployment, then $E[P|U = 1] = E[P|U = 0]$, so that the denominator equals 1. But, to the extent to which individuals learn about future unemployment and adjust their behavior accordingly, one needs to inflate the impact of unemployment on the first difference in consumption by the amount of information that is revealed over this time period.

5.2 2-Sample Implementation

I do not observe consumption concurrently with beliefs in the HRS samples. As a result, I estimate equation (11) using a 2-sample IV strategy. I estimate the numerator using consumption patterns in the PSID, largely following previous literature. I estimate the denominator using the subjective probability elicitation and unemployment data from the HRS.

5.2.1 Reduced Form

To estimate the numerator in equation (11), I follow Gruber (1997) and Chetty and Szeidl (2007) by regressing the change in log food expenditure on an indicator for unemployment. Panel 1 of Table IV presents the results. Consistent with Gruber (1997) and Chetty and Szeidl (2007), the event of unemployment leads to a roughly 6-9% lower food expenditure relative to the previous year. For the full sample, unemployment is associated with a 6.33% lower consumption

\footnote{This introduces potential selection bias into the estimated causal effect on consumption. Indeed, Online Appendix Figure V shows that individuals have (albeit small) predictive information about future unemployment 10 years in advance.}
(s.e. 0.533%), as shown in Column (1). However, to the extent to which those unemployed in year $t$ were also unemployed in $t - 1$, this may attenuate the difference in consumption. Column (2) limits the sample to those not unemployed in the year prior to the measurement of unemployment. The coefficient increases slightly to 0.0761 (s.e. 0.00849). Column (3) adds controls for the log change in household expenditure needs and the change in the number of household members to the specification in Column (2), yielding a coefficient of 0.0734 (s.e. 0.0086). Column (4) adds individuals fixed effects to the specification in Column (2). Column (5) limits the sample to those over age 40 to more closely align with the HRS sample for whom the private information is identified. These yields consumption drops of around 6-7%.

The analysis in columns (1)-(5) make a couple of specification decisions whose robustness are explored in Columns (6) and (7). First, outliers with more than a threefold change in food expenditure were dropped. Column (6) shows that re-introducing these observations increases the coefficient to -0.0951 (s.e. (0.0120). Second, I defined food expenditure as the sum of monthly food spending in the house, out of the house, and – in addition – any spending that occurred through food stamps. While this follows Zeldes (1989); Gruber (1997), there are two concerns with adding food stamp expenditure into the analysis. First, individuals may have already included this spending in their report for in- and out-of-house expenditure (although technically this would not be a correct response). Second, the wording of the food stamp question elicits concurrent expenditure for the previous week, whereas the food expenditure measures elicit a “typical” week. Since unemployment is co-incident with rises in food stamp use, this differential bias could lead to an under-stating of the impact of unemployment on food consumption.

To obtain a bound on this potential impact, Column (7) excludes food stamp expenditure from the food expenditure measure. Here, the expenditure drop is much larger (-0.164, s.e. 0.0158). This estimate is broadly more similar with estimates of Chodorow-Reich and Karabarbounis (2013), which also excludes food stamp expenditures. For the present purposes, it provides a bound on the size of the average expenditure drop.

Finally, note that the no trade condition in equation (6), the full no trade condition in equation (4) requires comparing the willingness to pay, $u'(c_u(p))$ to the pooled price ratio at each value of beliefs, $p$. It may be possible that people with some belief, $p$, have a greater ratio of marginal utilities than other types. While a full exploration of the joint distribution of the consumption drop and the likelihood of unemployment would require the joint distribution of the
elicitations and consumption, one can explore the potential impact of heterogeneity by looking at
the heterogeneity in the distribution of consumption. To this aim, Columns (7) and (8) report
estimates from the quantile regression of changes in log food expenditure on unemployment.
Column (7) reports the 10th percentile and Column (8) reports the 90th percentile. As can be
seen, unemployment is associated with a greater variance in food expenditure changes. It leads
to a 21% drop at p10 and a 3% increase at p90.

First Stage  Panel 2 of Table IV presents the estimates of the first stage in the denominator
of equation (11). To obtain this, I regress the subjective probability elicitation on an indicator
for subsequent unemployment. Even if the elicitations are noisy and biased measures of true
beliefs, this can continue to provide an estimate of $E[P|U=1] - E[P|U=0]$, as long as the
measurement error in $Z$ is uncorrelated with $U$ conditional on $P$.

The estimates suggest a coefficient of 0.197 (s.e. 0.012) when regressing the elicitation on the subsequent unemployment
indicator, which suggests roughly 80% of the uncertainty in unemployment is not known 1 year
in advance.

WTP Results  Panel 3 of Table IV reports the implied impact of unemployment on consump-
tion. For the baseline sample employed in $t-1$, unemployment leads to a 9.5% consumption
drop. For a coefficient of relative risk aversion of $\sigma = 2$, it implies an willingness to pay for
unemployment insurance of 18.9%. This is largely similar across specifications, but significantly
increases to 41% when not including food stamps in food expenditure as shown in Column (7).

Columns (8) and (9) show that this estimate rises to 52.8% for quantiles with the 90th
percentile of the consumption drop and is actually negative (-7.8%) for the 10th percentile
consumption drop. This suggests that there may be significant heterogeneity in the populations’
willingsness to pay for UI. But, all of these estimates remain well below the estimated 300%+
markups shown in Table III.

In short, the patterns are consistent with private information

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40 Because $P$ and $U$ are bounded variables, the classical measurement error assumption is unlikely to be literally
ture, but it is a useful benchmark.

41 Formally, this suggests individuals are not willing to pay to overcome the hurdles imposed by private information
for additional insurance beyond what is currently provided in the status quo world by the government, their firms, friends and family, and other sources of formal and informal insurance. Indeed, the distribution of beliefs, $P$, in the status quo world are precisely what is desired for measuring whether a private market for additional unemployment insurance would arise. But, it is also natural to ask whether a private market would arise if the government were to lower the amount of UI it provides.

To address this, Gruber (1997) also explores how this consumption drop varies with the level of government
unemployment benefits. Extrapolating to a world where the government provides no unemployment benefits,
being a micro-foundation for the absence of a private unemployment insurance market and potentially present a rationale for government intervention.

6 Optimal UI

If private information prevents the existence of a private UI market, then no one is willing to pay the pooled cost of worse risks in order to obtain additional insurance. Additional UI benefits would not deliver a Pareto improvement – some types \( \theta \) (e.g., the “good risks”) would be worse off, whereas other types (e.g., the “bad risks”) would be better off.\(^{42}\)

However, the endowment is not the only constrained-efficient allocation. A government can force the good risks to pay for insurance and accept utility levels below their endowment with no insurance. Traditional analyses of optimal social insurance solves for the optimal utilitarian policy – the level of benefits that maximizes the average level of utility across types, \( \theta \). This utilitarian metric can also be motivated from an ex-ante perspective of what level of UI benefits individuals would prefer prior to learning their type \( \theta \).

6.1 The Classical Case: No Private Heterogeneity

Before considering the optimal UI benefits in the present context, it is useful to begin with the canonical welfare analysis of UI without heterogeneous knowledge about future unemployment. In this case, Baily (1976) shows that the optimal level of UI benefits solves the implicit equation:

\[
\frac{u'}{v'} - 1 \approx \sigma \frac{\Delta c}{c} = FE
\]

where the LHS of equation (12) is the markup the individual is willing to pay for UI. Under state independent utility \((u = v)\), this is given by the consumption smoothing benefits, \(\sigma \frac{\Delta c}{c} = \sigma \frac{c-e}{c_e} \). The RHS of equation (12) is the fiscal externality, \(FE\), imposed by the behavioral response he shows the consumption drop would be roughly 25% (Table 1, p196). This would imply individuals would be willing to pay a 75% markup for insurance if they had a coefficient of relative risk aversion of \( \sigma = 3 \). This value continues to be of the order of magnitude of the estimated lower bounds for \( E \[T(P)\] \) and falls well below the estimated 300%+ markups for the point estimates for \( \inf T(p) \) in Section 4.2. In principle, changing the amount of government benefits could change the markups imposed by private information, \( T(p) \); however, the underlying fact that there appears to be a small fraction of people in every observable subgroup of the population that knows they are likely to lose their job would likely not be heavily affected; if anything, one might expect lower mean rates of unemployment entry which, as shown in Figure III, Panel F, would lead to higher markups that individuals would have to be willing to pay to cover the pooled costs of worse risks.

\(^{42}\) Although formally the no trade condition only considers single contracts, Appendix A.2 illustrates that the no trade condition also rules out menus of contracts so that there cannot be Pareto improvements from menus of insurance contracts either.
of individuals to the additional government UI benefits. It is often written as \( FE = \frac{\epsilon}{1-p} \) where \( \epsilon \) is the duration elasticity of unemployment and \( p \) is the probability of employment; more generally, the fiscal externality is simply the causal impact of the behavioral response to additional benefits, \( b \), financed by taxes, \( \tau \), on the government’s budget constraint (Chetty (2006); Hendren (2013a)).

In the absence of a micro-foundation for market non-existence, equation (12) characterizes not only the optimal insurance provided by the government, but also the optimal insurance provided by a competitive market. If \( \frac{\nu' - \nu'}{\rho'} > FE \), it would suggest private firms should be able to profitably provide additional insurance.

### 6.2 A Modified Baily-Chetty Condition

If individuals have knowledge about their future unemployment prospects, how does this change the optimality condition for UI? To begin, revisit the model in Section 2 and consider the optimal level of benefits, \( b \), financed with taxes \( \tau \). This maximizes a utilitarian welfare function,

\[
Q(\tau, b) = E[U(\tau, b; \theta)]
\]

subject to the budget constraint

\[
E[1 - p(\theta)]\tau - E[p(\theta)]b + E[N(a(\theta))] = 0
\]

where \( E[p(\theta)]b \) are the unemployment insurance payments, \( E[1 + p(\theta)]\tau \) are the taxes collected from the employed to pay for the unemployment benefits, and \( E[N(a(\theta))] \) is a placeholder that captures the net government budget impact of all other aspects of the individual’s behavior (captured in \( a(\theta) \)).\(^{44}\) In contrast to private free markets, the government need not respect any participation constraint: it can force everyone to pay premiums, \( \tau \), so that the budget constraint involves the entire population, as opposed to the adversely selected subset, \( \Theta \left( \frac{d\tau}{d\theta} \right) \).

It is straightforward to show that the level of \( b \) and \( \tau \) that maximizes utilitarian welfare

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\(^{43}\) This in principle includes impacts from extensive margin entry into unemployment (Feldstein (1978); Topel (1983)), improved wages from increased job match quality (Schneider et al. (2013); Nekoei and Weber (2015)), or fiscal impacts from changes in precautionary savings behavior (Engen and Gruber (2001)) or spousal labor supply (Cullen and Gruber (2000)).

\(^{44}\) I include this term to illustrate that the \( FE \) component of the Baily formula remains in this more general setup. For example, if \( a(\theta) \) includes spousal labor supply, \( N \) would include the net taxable income implications of this labor supply. If individuals can make choices that affect their future wages, \( N \) would include the net taxable income implications of those decisions.
solves the modified Baily-Chetty condition:

\[ W^{\text{Social}} = FE \]  

(13)

where

\[ W^{\text{Social}} = \frac{E \left[ \frac{p}{E[p]} u' \left( c_u \left( p \right) \right) \right]}{E \left[ \frac{(1-p)}{E[1-p]} v' \left( c_e \left( p \right) \right) \right]} - 1 \]  

(14)

so that \( W^{\text{Social}} \) is the markup over actuarially fair insurance that the social planner is willing to pay for additional UI, and \( FE \) is the fiscal externality associated with the policy.\(^{45}\) The intuition for the difference between equations (13) and (12) is straightforward. The envelope theorem implies individuals value additional benefits using their marginal utilities. The marginal utility of additional benefits to a type with probability \( p \) of experiencing unemployment is \( p u' \).

The cost to the government of providing an additional dollar of benefits is proportional to the

\[^{45}\text{To see this, note that the optimal allocation solves the first order condition:} \]

\[ \frac{\partial V}{\partial b} + \frac{\partial V}{\partial \tau} \frac{\partial \tau}{\partial b} = 0 \]

where

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

is the increased premium required to cover the cost of additional benefits, which includes the impact of the behavioral response, \( \frac{d}{db} \left[ \tau \frac{E[p(\theta)]}{1 - E[p(\theta)]} + T(a(\theta)) \right] \). 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 \( a(\theta) \). Also, note these responses are “policy responses” as defined in Hendren (2013a) – they are the behavioral response to a simultaneous increase in \( b \) and \( \tau \) in a manner for which the government’s budget breaks even.

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

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

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

So, the optimality condition becomes:

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

where

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

If only \( p \) is the margin of adjustment, then

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

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).
average probability of unemployment in the population, $E[p]$. If individuals are identical in their probabilities of experiencing unemployment (e.g., no one has unique knowledge about the event), then $p = E[p]$, and the formula reduces to the canonical formula in equation (12) with the average utilities $E[u']$ and $E[v']$ in place of $u'$ and $v'$.

In this sense, canonical willingness to pay measures for UI are identified using the variation in consumption resulting from the event of unemployment. But, from a social optimality perspective, UI also serves the role of providing insurance against the risk of future unemployment, $p(\theta)$. This simultaneously modifies the optimality formula and opens new methods to identify the value of UI by focusing on ex-ante behavioral responses to changes in the risk of future unemployment.

### 6.3 The Ex-ante Value of Insurance Against Risk of Unemployment

If individuals learn about future unemployment before the event occurs, it should effect behavior at the point when they learn (ex-ante relative to the job loss). Theory suggests that these ex-ante and ex-post behaviors are linked through the Euler equation (10). Let $c_{pre}(p)$ denote the consumption of an individual at the time when learning $\theta$. From the Euler equation (10),

$$v'(c_{pre}(1)) = u'(c_u(1))$$

$$v'(c_{pre}(0)) = v'(c_e(0))$$

Those who know they will lose their job should equate their marginal utility of consumption in the pre-period to the marginal utility of consumption when unemployed. Conversely, those that learn they will not lose their job should equate their pre-period marginal utility of consumption to the marginal utility of consumption when employed.

Consider the value of moving resources from those who learn ex-ante that they have a low risk of unemployment to those that learn they have a high risk of unemployment. One can define the welfare impact of UI across who learn ex-ante:

$$W_{ex-ante} = \frac{v'(c_{pre}(1)) - v'(c_{pre}(0))}{v'(c_{pre}(0))} \approx \frac{d\log(v'(c_{pre}(p)))}{dp}$$

$W_{ex-ante}$ evaluates the willingness to pay to move resources across states of the world to those that learn they are more likely to lose their job.
Ex-ante versus Ex-post  \( W^{ex-ante} \) is the markup individuals are willing to pay for insurance against the risk of learning they might lose their job, whereas \( W^{ex-post} \) is the average markup individuals are willing to pay for insurance against losing one’s job conditional on already learning \( \theta \). How do \( W^{ex-ante} \) and \( W^{ex-post} \) relate to each other?

**Case 1:** Suppose \( \frac{d \log(c_e)}{dp} = \frac{d \log(c_u)}{dp} = 0 \). Then, \( W^{ex-ante} = W^{Social} \).

Under the assumption that \( c_u \) and \( c_e \) do not systematically vary with \( p \), it is straightforward to see that \( v'(c_{pre}(1)) - v'(c_{pre}(0)) \) reveals the difference in marginal utilities between the unemployed and employed states. Hence, \( W^{ex-ante} \) reveals the ex-post willingness to pay for insurance against unemployment without ever requiring an assumption of state dependent utility across the unemployed and employed state. In this sense, \( W^{ex-ante} \) provides a new method for identifying the willingness to pay for unemployment insurance. Moreover, if utility is truly state independence, then the consumption impact of learning about future unemployment will be the same as the consumption impact of unemployment, so that these welfare measures will coincide.

More generally, it could be the case that there is a systematic variation between the marginal utility of consumption and the probability of future unemployment, \( p(\theta) \). For example, those who learn they might lose their job may also simultaneously learn that they face a permanent wage shock that affects lifetime income and reduces consumption in both the employed and unemployed states. In this case, there may be a greater insurance value to providing transfers to those that learn they may lose their job. Conversely, it could be the case that those that learn they may lose their job ex-ante have time to search for another job while still currently employed, which might improve their longer run job prospects and mitigate the negative impacts of the job loss.

If those with higher \( p \) have different consumptions when employed and unemployed, then \( W^{ex-ante} \) will differ from \( W^{ex-post} \). Yet, under the assumption that the change in equilibrium consumption is the same when employed or unemployed, one can write \( W^{Social} \) as a weighted average of \( W^{ex-ante} \) and \( W^{ex-post} \).

**Case 2:** Suppose \( \frac{d \log(c_e)}{dp} = \frac{d \log(c_u)}{dp} \) (but \( \frac{d \log(c_u)}{dp} \neq 0 \)) and \( u = v \). Then,

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

(16)

The next two sections presents two approaches to identifying ex-ante behavioral responses and estimating \( W^{ex-ante} \). One uses consumption drops in the years before unemployment; the
other uses spousal labor supply responses.

7 Consumption

One can estimate equation (15) using an assumption about the coefficient of relative risk aversion and an estimate of the impact of unemployment risk on consumption:

\[ W^{ex-ante} \approx \sigma_v \frac{d\log(c_{pre})}{dp} \]  

(17)

where \( \sigma_v = -\frac{v''c}{v'} \) is the coefficient of relative risk aversion (evaluated at \( c_{pre}(0) \)). \( W^{ex-ante} \) measures the percentage change in ex-ante marginal utilities from a percentile increase in the likelihood of unemployment.

While Section 5 explored the impact of unemployment on concurrent consumption growth, here I step back and explore the pattern of consumption around unemployment spells. For each year I construct the change in log food expenditure relative to the previous year, \( g_t = \log(c_t) - \log(c_{t-1}) \). Figure VII illustrates how food expenditure growth in year \( t+j \), \( g_{t+j} \), relates to the onset of unemployment in year \( t \) for \( j = -4, \ldots, 4 \). I regress \( g_{t+j} \) on an indicator for unemployment in year \( t \), controlling for a cubic in age and year dummy indicators. Panel A reports the pattern for the entire sample. Panel B restricts the sample to those who are not unemployed in years \( t-1 \) and \( t-2 \).

As noted in Table IV, there is a large consumption expenditure drop upon unemployment. The coefficients at \( j = 0 \) illustrate this 6-8% drop. But, consistent with the hypothesis that individuals can partially forecast their future unemployment, the onset of unemployment in year \( t \) is associated with a 2.5% lower consumption growth between year \( t-2 \) and \( t-1 \), despite those individuals not being unemployed in either of those periods.\(^{46}\)

To further explore the robustness of this pattern and quantify the magnitude of the expenditure drop in the 1-2 years prior to unemployment, Table V presents the results of a regression of the difference in log food expenditure in year \( t-2 \) and year \( t-1 \), \( \log(c_{t-1}) - \log(c_{t-2}) \), on an indicator for unemployment in current period. Column (1) includes controls for age and year dummies, analogous to the specification in Figure VII, Panel A. This shows a -0.0336 (s.e. 0.0057) drop in expenditure in the year before unemployment occurs. Column (2) restricts the

\(^{46}\)These estimates are similar to those found in Stephens (2001), who shows roughly a 2% drop in the year prior to unemployment. In contrast, I consider the impact of unemployment (as opposed to job loss) and restrict to a sample that is employed in \( t-1 \) and \( t-2 \).
sample to those who are not unemployed in years $t - 1$ and $t - 2$, analogous to the specification in Panel B of Figure VII. This attenuates the food expenditure drop slightly to -2.5% (s.e. 0.00942). This is to be expected, as unemployment status is autocorrelated at 0.387 across years in the baseline sample.

An additional concern is that household size or needs change around the time of unemployment. Column (3) of Table V adds controls for both the change in household size in years $t - 2$ versus $t - 1$ and also the change in expenditure needs, a variable available in the PSID that captures the total needs of the household based on its size and composition.\textsuperscript{47} This delivers a coefficient of -0.0249 (s.e. 0.0994), very similar to the -0.025 (s.e. 0.00942) coefficient in Column (2). Column (4) adds individual fixed effects to the specification in Column (2) and again delivers a coefficient of -0.0231 (s.e. 0.013), close to the -0.025 in Column (2). Column (5) restricts the sample to individuals over age 40 to more closely align with the HRS sample, which yields a coefficient of -0.0287 (s.e. 0.0151). Column (6) expands the sample to include outliers with more than threefold changes in food expenditure, yielding a coefficient of -0.0231 (s.e. 0.0121).

**Forward looking behavior versus correlated shocks** A key threat to identification of the ex-ante response to unemployment is that individuals are responding not to unemployment risk but rather to the impact of a correlated event. For example, if unemployment usually occurs after pay reductions at work, one might worry that the food expenditure reductions in period $t - 1$ relative to $t - 2$ are not individuals following their Euler equation, but rather are the result of hand-to-mouth consumers responding to changes in income.

To test for this potential concern, Column (7) adds controls for a third degree polynomial of changes in log household income to the baseline specification in Column (2). This yields a coefficient of 0.025 (s.e. 0.00935) nearly identical to the baseline specification in Column (2). Column (8) adds controls for a third degree polynomial of changes in log income of the household head, yielding a coefficient of -0.0248 (s.e. 0.0095).\textsuperscript{48} To understand why the results are not significantly affected by adding controls for income, Appendix Figure V replicates Figure V (Panel B) using log household income as the dependent variable as opposed to log food expenditure. For those employed in both $t - 2$ and $t - 1$, unemployment in period $t$ is not

\textsuperscript{47}For some years, the PSID also has food need measures available. Controlling for these reduces the sample size but delivers similar results.

\textsuperscript{48}The sample sizes are slightly lower for these specifications due to non-response to income questions. The food expenditure patterns are similar when restricting to a sample with non-missing income reports.
associated with any significant income change in any of the years prior to unemployment.\footnote{Note the levels of the coefficients are around -0.4 in the pre-periods, indicating that on average lower income populations are more likely to experience unemployment.} Overall, the results suggest that 1-2 years beforehand, individuals drop their consumption by about 2.5\% in response to the future the unemployment event.

**Evolution of Beliefs** To arrive at an estimate of $\frac{\partial \log(c_{pre})}{\partial p}$, the 2.5\% consumption drop needs to be scaled by the amount by which information is revealed between 2 and 1 year prior to the onset of unemployment event. Let $U_t$ denote an indicator for unemployment in year $t$. Let $P_{j,t}$ denote an indicator of the individuals beliefs at time $j \leq t$ about becoming unemployed in year $t$. The amount of information that is revealed by becoming unemployed in year $t - 1$ relative to $t - 2$ is given by:

$$\Delta_{\text{First Stage}} = E[P_{t-1,t}|U_t = 1] - E[P_{t-1,t}|U_t = 0] - E[P_{t-2,t}|U_t = 1] - E[P_{t-2,t}|U_t = 0]$$

Knowledge in $t - 1$ about $t$  
Knowledge in $t - 2$ about $t$

The first component of $\Delta_{\text{First Stage}}$ is precisely the first stage used in Section 5, and can be obtained by simply regressing the elicitations, $Z$, on an indicator for unemployment in the subsequent 12 months, $U$. This yields 0.197 (s.e. 0.0123). To subtract off the value of $E[P_{t-2,t}|U_t = 1] - E[P_{t-2,t}|U_t = 0]$, one would ideally have an elicitation about unemployment in the 12-24 months after the elicitation. Absent such an elicitation, one can proxy for this belief using the elicitation about the future 12 month unemployment to predict unemployment in the 12-24 months after the survey. This provides a correct estimate of $E[P_{t-2,t}|U_t = 1] - E[P_{t-2,t}|U_t = 0]$ if the error is uncorrelated with $U$ conditional on $P_{t-2,t}$, but it would likely under-state this value if the elicitation systematically lacks information about $U$ that is captured in the individuals true belief, $P_{t-2,t}$. In this sense, the first stage will likely be too large, leading to an under-statement of the willingness to pay for UI.

The second row of Appendix Table IV reports a value of $\Delta_{\text{First Stage}} = 0.0937$ (s.e. 0.0113), also shown in Online Appendix Figure V. People know more about their prospects for losing their job in the next 12 months than in the 12-24 months from now. The results suggest this difference-in-difference in beliefs between the unemployed and employed in years $t - 2$ and $t - 1$ is 0.1031 (s.e. 0.0159), as shown in the first row of Panel 2.\footnote{Online Appendix Figure V also reports the coefficients for future years of unemployment and obtains estimates of $E[Z_{t-j,t}|U_t = 1] - E[Z_{t-j,t}|U_t = 0]$ ranging from 0.1 to 0.05 at $j = 8$, which suggests most of the information}
Panel B of Table V scales the reduced form coefficients in Panel 1 by the first stage difference in beliefs of 0.1031. For the baseline specification in Column (2) using the sample that are employed in years $t-2$ and $t-1$, this yields a value of $\frac{d \log(c_{pre})}{dp} = 0.24$ (s.e. 0.09). This suggests learning one is 10\% more likely to lose their job would cause a 2.4\% drop in consumption. Scaling this estimate by a coefficient of relative risk aversion of $\sigma = 2$, it implies $W_{ex-ante} = 0.48$ (s.e. 0.18), which suggests individuals would be willing to pay a 48\% markup for additional unemployment insurance. The remaining columns illustrate the robustness of the estimates to other specifications. These results generally fall around 50\%.

8 Impact on Spousal Labor Supply

The previous section suggests individuals reduce their consumption in response to future unemployment. If the marginal utility of income increases, this should also increase activities that generate income, such as spousal labor supply. Here, I present evidence that the risk of future job loss increases spousal labor entry into the labor market.

Data As the analysis focuses on changes in spousal labor supply, I restrict the analysis using spousal labor supply to households married in both the current and previous wave of the survey. Spousal labor supply is defined as an indicator for the spouse working for pay in the current wave of the survey. I define labor market entry by the spouse as an indicator for the spouse working for pay in the current wave of the survey and not working for pay in the previous wave of the survey (2 years prior). Table I, Panel 3 presents the summary statistics for the sample. There are 11,049 observations from 2,214 households. Roughly 70\% of spouses are working for pay and 4\% of spouses go from not working to working between the previous and current wave of the survey (corresponding to a 2 year gap).

Results Figure IV plots the coefficients on bins of the subjective probability elicitations controlling for census region, year, age, age squared, gender, marital status, the log wage, and an indicator for the future realization of unemployment. Figure IV illustrates that those with higher elicitations are more likely to enter the labor force. Spouses of individuals with $Z > 50$ as opposed to $Z = 0$ are 2 percentage points more likely to enter the labor force. On the one in $Z$ is about unemployment in the subsequent year. This is consistent with a relatively flat consumption growth profile for years prior to $t - 2$ as shown in Figure V.
hand, this is a small effect: it suggests roughly 1 in 50 extra spouses are induced into the labor market when the spouse reported an elicitation above 50%, $Z > 50$. On the other hand, relative to the base entry rate of these spouses of 3.9%, it is quite large. For values $Z < 50$, the response is more muted. This is suggestive of a model in which labor market entry has high fixed cost, as would be implied by many labor market models.\footnote{The results are consistent with the findings of small ex-ante responses of spousal labor supply to subsequent unemployment in Stephens Jr (2002). The overall pattern is also consistent with the finding of Gruber and Cullen (1996) that higher levels of social insurance reduce the response of spouses into the labor market in response to unemployment. The presence of greater social insurance reduces the degree to which learning about future unemployment increases the marginal utility of income, which reduces the incentives to enter the labor force. Relative to this literature, I find that a large fraction of these responses occur even before the onset of unemployment.}

Table VI linearly parameterizes the relationship in Figure IV. Column (1) of Table VI presents this coefficient of 0.0282 (s.e. 0.00868). Column (2) restricts the sample to those who do not end up losing their job in the 12 months after the survey, yielding 0.0277 (s.e. 0.00896). This suggests households are responding to the risk of unemployment, even if the realization does not occur. Column (3) uses a specification that defines spousal work as an indicator for full-time employment, as opposed to any working for pay. This definition counts shifts from part-time to full-time work as labor market entry, as opposed to transitions to work for any pay. The pattern is largely similar, with a slope of 0.0278 (s.e. 0.00975).

There are a couple threats to interpreting the relationship as the impact of learning about future unemployment on labor supply. First, it could be that individuals who are more likely to lose their jobs also have spouses that perhaps have less labor force attachment and are more likely to come and go into the labor market. If true, it could generate a correlation between labor market entry and the elicitation purely because of a selection effect. To this aim, Column (4) considers a placebo test that uses the lagged measure of entry, which corresponds to the previous wave of the survey conducted 2 years prior. Here, the coefficient is 0.00464 (s.e. 0.00789) and is not statistically distinct from zero. Column (5) adds household fixed effects to the regression in Column (1) and Column (6) adds individual fixed effects to the specification in Column (1). The point estimates are quite stable, although noisy with the individual fixed effects.

Second it could be that the process that increased $Z$ is correlated with other shocks that are also correlated with labor supply preferences. This is fine if those shocks increase labor supply by increasing the marginal utility of consumption, but not if they do so by decreasing the marginal disutility of labor. In this sense, the fact that consumption falls suggests there
was not a general taste shift towards an increased value of leisure, but rather because of an expectation of lower future income.

In addition to impacts on entry, one may also expect to see fewer spouses leave the labor force in response to learning about future unemployment prospects for the other earner. However, one does not find much evidence of this pattern in the data. Column (7) defines labor market exit as an indicator for a spouse working for pay last wave and not working for pay in the current period. In contrast to the idea that spouses would be less likely to choose to enter the labor market, the coefficient of 0.0170 (s.e. 0.0116) is positive, although not statistically significant.

One possible explanation for why spouses are not less likely to stop working could be that it’s not their own choice; if a husband is likely to lose his job, the same set of circumstances may also affect the ability of the wife to stay in her job. To this aim, Column (9) shows that the the elicitation is positively related to spousal unemployment in the subsequent year, with a coefficient of 0.0250 (s.e. 0.00964). Spouses of those who learn they may lose their job may wish to keep their job, but may not always have that choice. In this case, the estimates for the impact of learning about future job loss on spousal labor supply under-state the response that would occur if the opportunity set available to the spouse were held fixed.

**Willingness to Pay** Under the assumption of an additively separable labor supply disutility, one can relate the size of the labor supply response to the labor supply response to a 1% increase in wages to arrive at a willingness to pay. Appendix D.2 shows that

\[ W^{ex-ante} \approx \frac{d\phi}{dp} \frac{1}{\epsilon_{semi}} \]  

(18)

where \( \frac{d\phi}{dp} \) is the percentage point increase in labor force participation resulting from a 1pp increase in \( p \), and \( \epsilon_{semi} \) is the semi-elasticity of spousal labor supply, equal to the percentage point increase in labor force participation that arises from a percentage increase in wages. The ratio of the impact of learning about unemployment relative to the impact of an increase in wages reveals the valuation of UI.

Panel 2 of Table VI translates the estimates into their implications for \( W^{ex-ante} \) using equation (18). To do so, I divide by the semi-elasticity of labor supply (here assumed to be 0.5, following Kleven et al. (2009)), and also correct for the fact that the regressions estimate \( \frac{d\phi}{dZ} \) as opposed to \( \frac{d\phi}{dp} \). Measurement error in \( Z \) induces attenuation bias. To do so, I scale the estimates
by \( \frac{\text{var}(Z|X)}{\text{var}(P|X)} \), where \( X \) are the controls in the regressions of labor force participation on \( Z \).\(^{52}\)

The results suggest that individuals would be willing to pay a 60% markup, \( W^{\text{ex-ante}} \approx 60\% \), for insurance against the event of learning they are going to lose their job in the baseline specification. The other specifications generate similar measures, which is not surprising given the stability of the regression coefficient in Panel 1. These estimates are also broadly similar to the implied willingness to pay based on the ex-ante consumption drop, and are also larger than the estimated ex-post willingness to pay based on consumption drops upon unemployment.

9 Social Welfare

The results for both consumption and labor supply ex-ante responses suggest that the ex-ante willingness to pay is larger than the ex-post willingness to pay, \( W^{\text{ex-ante}} > W^{\text{ex-post}} \). This suggests that the welfare value of UI is largest on the set of people who learn ex-ante that they may lose their job – precisely the set omitted in previous literature utilizing the impact of the event of unemployment to measure the willingness to pay for UI. It also suggests that those who learn ex-ante are experiencing shocks to lifetime earnings and consumption that also tend to lower their consumption in both the employed and unemployed states of the world. Appendix (C) explores this in more detail using the 10% sub-sample consumption module in the HRS and shows that a higher risk of unemployment is correlated with lower consumption ex-post even in the employed state of the world. This suggests incorporating a different insurance value for those who learn ex-ante (as is allowed in Case 2 above) is important for conducting welfare analysis.

This section estimates the welfare impact of UI using the formula in equation (16) that estimates \( W^{\text{social}} \) as a weighted average of \( W^{\text{ex-ante}} \) and \( W^{\text{ex-post}} \). Table VII presents the results for \( W^{\text{Social}} \) using the baseline specification assumptions\(^{53}\) in Tables IV-VI and a range of assumptions over the coefficient of relative risk aversion, \( \sigma \), and the semi-elasticity of spousal labor supply, \( \epsilon^{\text{semi}} \). For a coefficient of relative risk aversion of 2, the results suggest an ex-ante willingness to pay a markup of 48.5% against the realization of \( p \) but only a 18.9% markup against the realization of \( U \) given \( p \). This suggests that the total social value of insurance

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\(^{52}\) I construct \( \text{var}(Z|X) \) as the square of the RMSE of a regression of \( Z \) on the control variables. I construct \( \text{var}(P|X) \) as \( \text{var}(P|X) \approx \text{cov}(Z,L|X) \), where the approximation would hold exactly if the measurement error in \( Z \) were classical. To construct \( \text{cov}(Z,L|X) \), I first residualize \( L \) and \( Z \) on \( X \) and then calculate the covariance of the residuals, then adjust for the degrees of freedom introduced in the initial residualization.

\(^{53}\) In particular, I use the specification in Column (2) of Tables IV and VI that restrict to individuals employed in \( t-1 \). I use the specification in Table V, Column (1).
is 24.8%. Column (4) presents the baseline results using the ex-ante labor supply response to measure the ex-ante willingness to pay for UI. This yields a willingness to pay of 60.2%; combining this with the ex-post willingness to pay of 18.9% yields a total willingness to pay of 27.1%.

The remaining columns illustrate the robustness of the results to varying assumptions about the coefficient of relative risk aversion and the semi elasticity of spousal labor supply. Increasing the coefficient of relative risk aversion to 3 or reducing the spousal labor supply elasticity to 0.25 suggests that the behavioral responses of consumption and labor supply are more costly from a welfare perspective, and increase the willingness to pay to roughly 35%. Conversely, if risk aversion is closer to 1 or the elasticity of spousal labor supply is higher (e.g. 0.75) it can reduce the social willingness to pay below 25%.

Of course, the precise willingness to pay for UI is sensitive to assumptions about $\sigma$ and $\epsilon_{semi}$; but the evidence suggests that the ex-ante value of insurance – the component largely ignored in previous literature – is larger than the value of the ex-post insurance against the realization of unemployment. Incorporating the ex-ante insurance value against the risk of unemployment increases the social value of unemployment insurance.

10 Conclusion

This paper argues that private information prevents the existence of a robust private market for unemployment or job-loss insurance. Unless individuals are willing to pay extreme markups, the empirical results are consistent with the absence of a private market.

This micro-foundation motivates a modification to the formulas characterizing the utilitarian-optimal unemployment insurance benefit level. If individuals learn about unemployment before it actually occurs, they may value insurance against the risk of becoming unemployed, not only insurance against the realization of unemployment conditional on their own risk. While traditional welfare analyses miss this value of insurance, the presence of ex-ante responses yields new methods to estimate the willingness to pay for UI that exploit the response to information.

The approaches can be applied to other settings, such as disability insurance, social security, and health insurance contexts. In particular, the 2-sample IV procedure to estimate willingness to pay developed in Section 5 and 7 shows one can conduct such welfare analysis without simultaneously observing consumption and beliefs. In this sense, I hope the analyses in this
paper provides a path forward for motivating a micro-foundation for government intervention and the calculation of the optimal social insurance.

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A No Trade Condition

A.1 Multi-Dimensional Heterogeneity

This section considers the case in which there does not exist a one-to-one mapping between \( \theta \) and \( p(\theta) \) so that there is potentially heterogeneous willingness to pay for additional UI for different types \( \theta \) 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 \( \theta \) that are willing to pay for this policy:

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

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

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

so that the average probability of the types selecting \( \frac{d\tau}{db} \) is equal to the average cost of types above \( \tilde{p}\left(\frac{d\tau}{db}\right) \). Note that \( \tilde{p} \) can be constructed to be strictly increasing in \( \frac{d\tau}{db} \) so that \( p^{-1} \) exists.

I construct \( f(p) \) as follows. Define \( A \) to be the range of \( \tilde{p} \) when taking values of \( \frac{d\tau}{db} \) ranging from 0 to \( \infty \). Without loss of generality, each value of \( \frac{d\tau}{db} \) generates a different value of \( p = \tilde{p}^{-1}(p) \). I assign \( f(p) \) to each of these types as the value of \( \theta \) such that

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

which amounts to testing the no trade condition.

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 we 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 (2013b), then apply the no trade condition to rule out menus. Loosely, the present model is effectively the same model as in Hendren (2013b) aside from the introduction of a moral hazard problem and endogenous marginal utilities, \( u' \) and \( v' \). I assume here that there is no heterogeneity in the marginal utilities across types and leave future work to study the problem of menus when individuals are making a range of additional choices. With this simplification, the only distinction relative to Hendren (2013b) is the introduction of the moral hazard problem in choosing \( p \). Below, I show that introducing a moral hazard problem can’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 (2013b) can be applied to rule out menus.

I abstract from individual heterogeneity in the utilities, \( u(c) \) and \( v(c) \), and assume for simplicity that consumption in the state of employment and unemployment is given exogenously and common across all types. I also assume individuals only choose \( p \) (i.e. there is no \( a(\theta) \) choice). Introducing such behavioral responses and heterogeneity in utilities would likely be straightforward, but introduce a range of technical assumptions that would need to be included to rule out non-marginal insurance deviations. I leave a detailed treatment of this no trade condition under menus for future work.

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, \( \pi \), subject to the incentive and participation constraints.

The insurer can offer a menu of contracts, \( \{\nu(\theta), \Delta(\theta)\}_{\theta \in \Gamma} \) where \( \nu(\theta) \) specifies a total utility provided to type \( \theta \) and \( \Delta(\theta) \) denotes the difference in utilities if the agent becomes unemployed. Note that \( \nu(\theta) \) implicitly contains the disutility of effort.

For exposition of the proof, I switch focus from the probability of unemployment, \( \hat{p} \), to \( \hat{q} \), which we define to be the probability of employment,

\[
\hat{q}(\Delta; \theta) = 1 - \hat{p}(\Delta; \theta)
\]

so that the agent’s effort cost is \( \Psi(\hat{q}(\Delta; \theta) \theta) \). Note that a type \( \theta \) that accepts a contract containing \( \Delta \) will choose a probability of employment \( \hat{q}(\Delta; \theta) \) consistent with the first order
condition $\Psi' (\hat{q} (\Delta; \theta ) ; \theta ) = \Delta$.

Now, let $\pi (\Delta, \nu; \theta )$ denote the profits obtained from providing type $\theta$ with contract terms $\nu$ and $\Delta$, given by

$$\pi (\Delta, \nu; \theta ) = \hat{q} (\Delta; \theta ) (c_e - C_e (\nu - (\psi (\Delta; \theta ))) + (1 - \hat{q} (\Delta; \theta )) (c_u - C_u (\nu - \Delta - (\psi (\Delta; \theta ))))$$

where $C_u = u^{-1}$ and $C_e = v^{-1}$. Note that the profit function takes into account how the agents’ choice of $p$ varies with $\Delta$.

Throughout, I maintain Assumption A.3: that $\pi$ is concave in $(\nu, \Delta)$. Below in Section A.4, I discuss primitives for such concavity.

I prove the sufficiency of the no trade condition for ruling out trade by mapping it into the setting of Hendren (2013b) and applying his proof. 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 $\nu$ 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

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

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

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

and in the world in which $p$ is not affected by $\Pi$,

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

So, for small variations in $\nu$ and $\Delta$, we have that

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

because insurance causes an increase in $p$. Now, Hendren (2013b) shows that the no trade condition implies that $\tilde{\Pi} \leq 0$ for all menus, $\{ \nu (\theta) , \Delta (\theta) \}$. Therefore, the no trade condition also implies $\Pi \leq 0$ for local variations in the menu $\{ \nu (\theta) , \Delta (\theta) \}$ 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 $\Delta$, so that sufficiently small values of insurance allow for a profitable insurance contract to be traded.

### A.3 Concavity Assumptions

Heretofore, I have placed no restrictions on either the nature of the distribution of types, $\theta$, or the structure of the effort function, $\Psi$. This allows for considerable generality in characterizing when insurance markets can exist with moral hazard and adverse selection. But, 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. Fortunately, a simple condition ensures that a local variational analysis provides a global characterization of the existence of profitable deviations from the endowment. Intuitively, the needed condition to ensure sufficiency of a local analysis is that the marginal profitability of insurance declines in the amount of insurance provided.

To express this condition, let $\Delta$ denote the difference in utilities between being employed and unemployed, so that lower values of $\Delta$ correspond to greater amounts of insurance. Define $\hat{p}(\Delta; \theta)$ to be the induced probability of unemployment for type $\theta$, which solves

$$\Psi'(1 - \hat{p}(\Delta; \theta); \theta) = \Delta$$

It is straightforward to show that $\hat{p}$ is decreasing in the size of the incentives to work, $\Delta$. Now, define the cost functions,

$$C_u(x) = u^{-1}(x)$$
$$C_v(x) = v^{-1}(x)$$

$C_u(x)$ measures the amount of consumption required to provide $x$ units of utility when unemployed; similarly, $C_v(x)$ measures the amount of consumption required to provide $x$ units of utility when employed.

Now, let $\pi(\Delta, \mu; \theta)$ denote the profit obtained from type $\theta$ if she is provided with total utility $\mu$ and difference in utilities $\Delta$,

$$\pi(\Delta, \mu; \theta) = (1 - \hat{p}(\Delta; \theta)) (c^e_v - C_v(\mu - \Psi (1 - \hat{p}(\Delta; \theta)))) + \hat{p}(\Delta; \theta) (c^e_u - C_u(\mu - \Delta - \Psi (1 - \hat{p}(\Delta; \theta))))$$
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 $\pi(\Delta, \mu; \theta)$ is concave in $(\Delta, \mu)$.

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

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 $\Delta$), then concavity of the utility functions, $u$ and $v$, imply concavity of $\pi(\Delta, \mu; \theta)$. Assumption A.3 ensures that the ability of agents to choose $p$ does not induce regions in which the marginal profitability of insurance actually increases in the amount of insurance.

### A.4 Sufficient Conditions for Concavity

Assumption A.3 maintains that $\pi$ is globally concave in $(\mu, \Delta)$. Here, we derive sufficient conditions on the primitives of the model that guarantee this concavity. In particular, we show that if $\Psi'''(q; \theta) > 0$ and $\frac{u'\left(c_e^e\right)}{v\left(c_u^u\right)} \leq 2$ then $\pi$ is globally concave in $(\mu, \Delta)$.

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

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

Our goal is to show the Hessian of $\pi$ is negative semi-definite. We proceed in three steps. First, we derive conditions which guarantee $\frac{\partial^2 \pi}{\partial \Delta^2} < 0$. Second, we show that, in general, we have $\frac{\partial^2 \pi}{\partial \mu^2} < 0$. Finally, we 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.4.1 Conditions that imply $\frac{\partial^2 \pi}{\partial \Delta^2} < 0$

Taking the first derivative with respect to $\Delta$, we have

$$\frac{\partial \pi}{\partial \Delta} = \frac{\partial \hat{q}}{\partial \Delta} \left( c_e^e - C_e(\mu - \Delta - \Psi(\hat{q}(\Delta))) \right)$$

$$- (1 - \hat{q}(\Delta)) C'_u(\mu - \Delta - \Psi(\hat{q}(\Delta))) - \hat{q}(\Delta) C'_e(\mu - \Psi(\hat{q}(\Delta)))$$
Taking another derivative with respect to $\Delta$, applying the identity $\Delta = \Psi'(\hat{q}(\Delta))$, and collecting terms yields
\[
\frac{\partial^2 \pi}{\partial \Delta^2} = - \left[ (1 - \hat{q}(\Delta)) (1 + \Delta)^2 C''_{\mu} (\mu - \Delta - \Psi(\hat{q}(\Delta))) + \hat{q}(\Delta) (\Delta'\Delta') (\Delta'' (\mu - \Psi(\hat{q}(\Delta)))) \right] \\
+ \frac{\partial \hat{q}}{\partial \Delta} \left[ (1 - \hat{q}(\Delta)) C'(\mu - \Delta - \Psi(\hat{q}(\Delta))) + \hat{q}(\Delta) C'(u - \Psi(\hat{q}(\Delta))) \right] - (2 + 2\Delta'\Delta') C'(\mu - \Delta - \Psi(\hat{q}(\Delta))) \\
+ \frac{\partial^2 \hat{q}}{\partial \Delta^2} \left[ c_{e}^e - c_{e}^e + C(\mu - \Delta - \Psi(\hat{q}(\Delta))) - C(\mu - \Psi(\hat{q}(\Delta))) + (1 - \hat{q}(\Delta)) \Delta C'(\mu - \Delta - \Psi(\hat{q}(\Delta))) \right]
\]

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
\[
\frac{u'(c_{e}^e)}{v'(c_{e}^e)} \leq 2
\]
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 positive. In sum, it is sufficient to assume $\frac{u'(c_{e}^e)}{v'(c_{e}^e)} \leq 2$ and $\Psi''' > 0$ to guarantee that $\frac{\partial^2 \pi}{\partial \Delta^2} < 0$.

### A.4.2 Conditions that imply $\frac{\partial^2 \pi}{\partial \mu^2} < 0$

Fortunately, profits are easily seen to be concave in $\mu$. 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.4.3 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
\[
\frac{\partial^2 \pi}{\partial \mu \partial \Delta} = (1 - \hat{q}(\Delta)) C''(\mu - \Delta - \Psi(\hat{q}(\Delta))) (1 + \Delta'\Delta') + \hat{q}(\Delta) C''(\mu - \Psi(\hat{q}(\Delta))) \Delta'\Delta'
\]
Also, we note that under the assumptions $\Psi'' > 0$ and $\frac{u'(c^e)}{v'(c^e)} \leq 2$, we have the inequality

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

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 $\frac{\partial^2 \pi}{\partial \Delta^2}$ and subtract $\left(\frac{\partial^2 \pi}{\partial \Delta^2}\right)^2$. Fortunately, many of the terms cancel out, leaving the inequality

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

which reduces to the inequality

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

where

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

$$= 1$$

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

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

A.4.4 Summary

As long as $\Psi''' > 0$ and $\frac{u'(c^e)}{v'(c^e)} \leq 2$, the profit function is guaranteed to be concave. As noted in the text, generally one finds empirically that $\frac{u'(c^e)}{v'(c^e)} \leq 2$. 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 work incentives on the employment probability is declining in the size of the work incentives.

Future work can derive the necessary conditions when the willingness to pay for additional UI varies conditional on $p$ and 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.
B Proof of Proposition 1

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

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

Proof: note that

\[
m(P) = E[P - \hat{p}|P \geq p]
\]

so that

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

So, we wish to show that

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

Note that:

\[
E \left[ \frac{m(P)}{P} \right] = E \left[ \frac{1}{1 - F(P)} \int (\hat{p} - P) f(\hat{p}) d\hat{p} \right] = E \left[ \frac{E[\hat{p}\hat{p} \geq P]}{P} \right] - 1 = E_{P} \text{E}_{\hat{p}} \left[ \frac{\hat{p}}{P}, \frac{\hat{p}}{P} \geq 1 \right] - 1
\]

And:

\[
\frac{E[m(P)]}{E[P]} = \frac{E_{P} E_{\hat{p}} [\hat{p} | \hat{p} \geq P]}{E[P]} - 1
\]

So, we wish to test whether

\[
E_{P} \text{E}_{\hat{p}} \left[ \frac{\hat{p}}{E[P]}, \hat{p} \geq P \right] < ? \ E_{P} \text{E}_{\hat{p}} \left[ \frac{\hat{p}}{P}, \hat{p} \geq P \right]
\]

or

\[
E_{P} \text{E}_{\hat{p}} \left[ \frac{\hat{p}}{P} - \frac{\hat{p}}{E[P]} | \hat{p} \geq P \right] > ? 0
\]

or

\[
E_{P} \text{E}_{\hat{p} \geq P} \left[ \frac{\hat{p}}{P} \left( \frac{1}{P} - \frac{1}{E[P]} \right), \hat{p} \geq P \right] > ? 0
\]

Note that once we’ve conditioned on \( \hat{p} \geq P \), we can replace \( \hat{p} \) with \( P \) and maintain an inequality

\[
E_{P} \text{E}_{\hat{p} \geq P} \left[ \frac{\hat{p}}{P} \left( \frac{1}{P} - \frac{1}{E[P]} \right), \hat{p} \geq P \right] \geq E_{P} \text{E}_{\hat{p} \geq P} \left[ P \left( \frac{1}{P} - \frac{1}{E[P]} \right), \hat{p} \geq P \right]
\]

\[
\geq E_{P} \text{E}_{\hat{p} \geq P} \left[ 1 - \frac{P}{E[P]} | \hat{p} \geq P \right]
\]

\[
\geq E_{P} \left[ 1 - \frac{P}{E[P]} \right]
\]

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

**Proof of Proposition.**

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

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

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

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

so that

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

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

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

so that

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

which is the desired result.

**C Consumption Response of $c_u$ and $c_e$**

**C.1 Data**

I explore whether knowledge about future unemployment impacts consumption after the event of unemployment is realized, $c_u(p)$ and $c_e(p)$. To do so, I rely on the consumption mail survey component of the HRS, which is mailed to roughly 10% of respondents. It provides information on a range of consumption variables that are aggregated in a cross-year file constructed by RAND. It is administered 1 year after the core survey and asks about consumption expenditure in the previous 12 months. Hence, it provides a measure of consumption in the time period corresponding to the unemployment measure, $U$. 

---

55
Table I, Panel 3 presents the summary statistics for the consumption sample. There are 2,798 observations from 862 households. The consumption module is asked of the entire household. To account for differences in household size, I present results for both aggregate household consumption and per capita consumption, which is household consumption divided by the total number of household members. All standard errors are clustered at the household level.

C.2 Results

Online Appendix Figure III plots the relationship between group indicators of the subjective probability elicitations and log per capita consumption expenditure (Panel A) and log consumption expenditure (Panel B). The regression includes controls for census region, year, age, age squared, gender, marital status, the log wage, and – most importantly – an indicator for the future realization of unemployment. As shown in the figure, there is an decreasing pattern over the range $Z > 0$: individuals with higher subjective probability elicitations have lower consumption. Consistent with the measurement error model in Section 4.2 that suggests most of the reports of $Z = 0$ reflect a point bias that would have otherwise had higher values of $Z$, we obtain a lower coefficient at $Z = 0$.

Motivated by the non-parametric pattern in Online Appendix Figure III, Appendix Table IV reports the regression coefficient on $Z$, combined with a dummy indicator for $Z = 0$. These variables are interacted with an indicator of subsequent unemployment $U$. Column (1) reports the negative coefficient of $-0.16$ (s.e. 0.0781) for the per capita consumption specification for those who do not experience unemployment. Those who believe they are more likely to become unemployed have lower consumption even if they do not become unemployed. This pattern is precisely what can lead to the canonical Baily formula under-stating the value of social insurance. The coefficient on the interaction with unemployment is negative, $-0.137$ (s.e. 0.268), but not statistically significant. This should not be too surprising given the fact that roughly 3% of households actually experience unemployment. The negative coefficient on $1 \{Z = 0\}$ of $-0.0893$ (s.e. 0.0334) is consistent with the pattern in Figure IV in which the consumption expenditure values at $Z = 0$ fall below the pattern generated by the positive elicitations.

Column (2) reports the results using household consumption instead of household consumption per capita. This yields a coefficient of $-0.110$ (s.e. 0.0596) on the elicitation for those who do not experience unemployment. Here, the coefficient on the unemployment interaction
with the elicitation is statistically significant, $-0.421$ (s.e. 0.207), but is arguably too large for credibility and has a very wide standard error. Column (3) restricts the sample to those who have positive elicitations and illustrates that the results are quite similar to the baseline specification in Column (1). Column (4) restricts the sample to those who do not experience unemployment; here again, the coefficients are similar to the baseline specification. Column (5) considers non-durable consumption instead of total consumption expenditure, and finds a negative coefficient of $-0.162$ (s.e. 0.0789) that is again similar to the baseline specification.

Column (6) drops the control variables in the analysis. Here, we end up with a larger coefficient of $-0.345$ (s.e. 0.0798) from the analysis. A key concern with this specification is that the variation in beliefs captures heterogeneity in people (e.g. low versus high wage workers) as opposed to learning about the event. I return to the distinction between selection and information realization below.

Finally, column (7) illustrates the fragility of the results to the inclusion of the indicator for $Z = 0$. As shown in Figure IV, the negative relationship is quite nonlinear. While this pattern is consistent with focal point bias so that many of those responding $Z = 0$ are drawn from a population who otherwise would have said a much larger value of $Z$, dropping these controls renders the negative slope insignificant at -0.04 (s.e. 0.0659).

**Selection versus the effect of information realization** The cross-sectional relationship between the ex-ante subjective elicitations and consumption could reflect either the impact of learning about future unemployment on consumption, or be the result of a general correlation across the income distribution between job stability and income levels. Although the regressions control for the individual’s wages, there of course could be measurement error in the survey, or it could be that many years of lagged wages are relevant.\(^{54}\)

To disentangle whether the patterns in Online Appendix Figure III and Appendix Table IV reflect an impact of information revelation about future unemployment or a cross-sectional selection pattern, Online Appendix Figure IV, Panel A, presents the coefficients on the elicitation, $Z$, using leads and lags of log household consumption expenditure per capita. I include controls

\(^{54}\)If the pattern reflects selection between high and low income individuals, the covariance calculations for the optimal degree of unemployment insurance would be valid as measuring the benefits from additional UI, but one would want to take into account the impact of UI on the effective total amount of redistribution in the economy and include the associated fiscal externalities akin to the redistributive costs associated with the progressive income tax schedule (Kaplow (2008); Hendren (2014)).
for unemployment status and an indicator for a focal point response of $Z = 0$. For simplicity, I summarize the negative relationship between $Z$ and log consumption expenditure by pooling across unemployment status and do not interact $Z$ with $U$.

Online Appendix Figure IV, Panel A, reveals that higher values of subjective probability elicitations do not correspond to lower values of consumption when measuring consumption in the years prior to the elicitation (conditional on the controls for census region, year, age, age squared, gender, marital status, and the log wage). Rather, the onset of the realization of information about a greater likelihood potential unemployment leads to lower consumption in the years subsequent to the information revelation. This is consistent with the idea that the pattern in Online Appendix Figure III is largely capturing the impact of information shocks on consumption, as opposed to a persistent heterogeneity in consumption across the population who report high versus low elicitations, $Z$.

Panel B replicates the analysis on the subsample with positive elicitations only ($Z > 0$), corresponding to column (3) in Table IV. Panels C and D replicate the analysis using household consumption instead of per capita consumption. Across all specifications, we find the pattern that consumption appears to drop at the point of learning about future likely unemployment, even conditional on whether or not that unemployment actually occurs.

D Welfare Metrics

D.1 IV Derivation

This section shows that scaling the impact of unemployment on consumption growth by the amount of information revealed in that one-year period yields an estimate of the causal effect of unemployment on consumption. I allow $c_e$ and $c_u$ to vary with $p$, but I assume $\frac{d\log(c_e(p))}{dp} = \frac{d\log(c_u(p))}{dp} = \frac{-d\log(c_{post})}{dp}$ is constant. Note under state dependence, the Euler equation implies

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

so that

$$u''(c_{pre}(p)) \frac{dc_{pre}}{dp} = u'(c_u(p)) - u'(c_e(p)) + pu''(c_u(p)) \frac{dc_u}{dp} + (1 - p) u''(c_e(p)) \frac{dc_e}{dp}$$
Now, taking expectations (with respect to $\theta$) and taking a Taylor expansion for $u'$ (ignoring $u'''$ terms, as is common in existing literature) yields

$$\sigma \frac{-d \log (c_{\text{pre}})}{dp} = \sigma (-E [\log (c_e) - \log (c_u)]) + \sigma \frac{-d \log (c_{\text{post}})}{dp}$$

So, under a Taylor approximation with small $u'''$ terms reveals that the impact of beliefs on ex-ante consumption equal the average difference in consumption across unemployed and employed states plus the ex-post consumption impact of beliefs:

$$-d \log (c_{\text{pre}}) = -E [\log (c_e) - \log (c_u)] + -d \log (c_{\text{post}})$$

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

$$\Delta^{FD} = E [\log (c_{\text{post}}) - \log (c_{\text{pre}}) | U = 1] - E [\log (c_{\text{post}}) - \log (c_{\text{pre}}) | U = 0]$$

Note that $c_{\text{post}} = c_u$ for those with $U = 1$ and $c_{\text{post}} = c_e$ for those with $U = 0$. Hence,

$$\Delta^{FD} = E [\log (c_u) - \log (c_e) | U = 1] + E [\log (c_e (p)) | U = 1] - E [\log (c_e (p)) | U = 0] - (E [\log (c_{\text{pre}}) | U = 1] - E [\log (c_{\text{pre}}) | U = 0])$$

Note that the impact of $p$ does not change the percentage difference in consumption between employed and unemployed states, so that $E [\log (c_u) - \log (c_e) | U = 1] = E [\log (c_u) - \log (c_e)]$ is the average causal effect of unemployment on consumption. Now, using the linearity assumptions for $\frac{d \log (c_{\text{pre}})}{dp}$ and $\frac{d \log (c_{\text{post}})}{dp}$ yields

$$\Delta^{FD} = E [\log (c_u) - \log (c_e)] + \left[ \frac{d \log (c_{\text{post}})}{dp} - \frac{d \log (c_{\text{pre}})}{dp} \right] (E [P|U = 1] - E [P|U = 0])$$

Using the Euler equation yields

$$\frac{d \log (c_{\text{post}})}{dp} - \frac{d \log (c_{\text{pre}})}{dp} = E [\log (c_e) - \log (c_u)]$$

so that

$$\Delta^{FD} = E [\log (c_u) - \log (c_e)] (1 - (E [P|U = 1] - E [P|U = 0]))$$

or

$$E [\log (c_u) - \log (c_e)] = \frac{\Delta^{FD}}{1 - E [P|U = 1] - E [P|U = 0]}$$
D.2 Ex-ante labor supply derivation

We also observe labor supply responses by households in response to these shocks. If we assume a spouse labor supply decision, \( l \in \{0,1\} \), is contained in the set of other actions, \( a \). Suppose this earns income, \( y \). Then, we can use the spousal labor supply response, combined with known estimates of the spousal labor response to labor earnings to back out the implied value of social insurance. Let

\[
\Psi (1 - p, a, \theta) = \tilde{\Psi} (1 - p, \tilde{a}, \theta) + 1 \{ l = 1 \} \eta (\theta)
\]

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

Let \( k(y, l, p) \) denote the 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

\[
k(y, 1, p) - k(0, 0, p) \geq \eta (\theta)
\]

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 \( \eta (\theta) \leq \bar{\eta} (y, p) \) and the labor force participation rate is given by \( \Phi (y, p) = F (\bar{\eta} (y, p)) \).

Now, note that

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

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

\[
\frac{d \Phi}{dp} \approx f (\bar{\eta}) \frac{\partial^2 k}{\partial p^2} y
\]

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

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

and integrating across all the types \( p \), we have

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

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,

\[ \mathbb{E}_p \left[ \frac{d \Phi}{dp} \right] \approx \mathbb{E}_p \left[ \frac{d \Phi}{dy} y \frac{d}{dp} v \left( c_{pre}(p) \right) \right] \]

Now, let \( \epsilon_{semi} = \frac{d \Phi}{d \log(y)} \) denote the semi-elasticity of spousal labor force participation. We therefore have

\[ \frac{\mathbb{E}_p \left[ \frac{d \Phi}{dp} \right]}{\epsilon_{semi}} \approx \mathbb{E}_p \left[ \frac{d}{dp} v \left( c_{pre}(p) \right) \right] \]

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 \( \frac{f(1) - f(0)}{f(0)} \approx \frac{d}{dx} \log(f) \), we have

\[ \frac{\mathbb{E}_p \left[ \frac{d \Phi}{dp} \right]}{\epsilon_{semi}} \approx \frac{v'(1) - v'(0)}{v'(0)} \]

Now, how do we estimate \( \frac{d \Phi}{dp} \)? We see \( \Phi(Z) \). regressing \( l \) on \( Z \) will generate an attenuated coefficient. To first order, we can inflate this by the ratio of the variance of \( Z \) to the variance of \( P \), or

\[ \frac{v'(1) - v'(0)}{v'(0)} \approx \beta \frac{\text{var}(Z)}{\epsilon_{semi} \text{var}(P)} \]

D.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 \( \frac{d \log(c_u)}{dp} = \frac{d \log(c_e)}{dp} = \frac{d \log(c_{post})}{dp} \)

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

\[ W_{Social} + 1 = \frac{E \left\{ \frac{\bar{p}}{1 - \bar{p}} u'(c_u) \right\}}{E \left\{ \frac{\bar{p}}{1 - \bar{p}} u'(c_e) \right\}} \]

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

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

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
\[
\text{cov} \left( \frac{p}{\bar{p}}, \frac{u'(c_u)}{E[u'(c_u)]} \right) = \text{cov} \left( \frac{p}{\bar{p}}, \frac{u'(\bar{c}_u) + u''(\bar{c}_u)(c_u - \bar{c}_u)}{u'(c_u)} \right) \\
\approx -\sigma \text{cov} \left( \frac{p}{\bar{p}}, \frac{(c_u - \bar{c}_u)}{\bar{c}_u} \right) \\
\approx -\sigma \text{cov} \left( \frac{p}{\bar{p}}, \log (c_u) \right) \\
\approx -\sigma \frac{\text{var}(p) \text{dlog}(c_{\text{post}})}{\bar{p}} \\
\]
Similarly,
\[
\text{cov} \left( \frac{p}{1 - \bar{p}}, \frac{u'(c_e)}{E[u'(c_e)]} \right) \approx -\sigma \frac{\text{var}(p) \text{dlog}(c_{\text{post}})}{1 - \bar{p}} \\
\]
So that
\[
\text{cov} \left( \frac{p}{\bar{p}}, \frac{u'(c_u)}{E[u'(c_u)]} \right) + \text{cov} \left( \frac{p}{1 - \bar{p}}, \frac{u'(c_e)}{E[u'(c_e)]} \right) \approx -\sigma \frac{\text{var}(p) \text{dlog}(c_{\text{post}})}{\bar{p} (1 - \bar{p})} \\
\]
and note
\[
\frac{\text{var}(p)}{\bar{p} (1 - \bar{p})} = E[P|U = 1] - E[P|U = 0] \\
\]
(think of a regression of $p$ on $U$). Therefore,
\[
\text{cov} \left( \frac{p}{\bar{p}}, \frac{u'(c_u)}{E[u'(c_u)]} \right) + \text{cov} \left( \frac{p}{1 - \bar{p}}, \frac{u'(c_e)}{E[u'(c_e)]} \right) \approx \sigma \frac{-\text{dlog}(c_{\text{post}})}{\text{dp}} (E[P|U = 1] - E[P|U = 0]) \\
\]
Now, Section D.1 shows that the Euler equation implies $\frac{-\text{dlog}(c_{\text{post}})}{\text{dp}} + E[\log (c_e) - \log (c_u)] \approx \frac{-\text{dlog}(c_{\text{pre}})}{\text{dp}}$, so that
\[
\text{cov} \left( \frac{p}{\bar{p}}, \frac{u'(c_u)}{E[u'(c_u)]} \right) + \text{cov} \left( \frac{p}{1 - \bar{p}}, \frac{u'(c_e)}{E[u'(c_e)]} \right) \approx \sigma \left[ \frac{-\text{dlog}(c_{\text{pre}})}{\text{dp}} - E[\log (c_e) - \log (c_u)] \right] (E[P|U = 1] - E[P|U = 0]) \\
\]
Additionally, note that
\[
\frac{E[u'(c_u)]}{E[u'(c_e)]} \approx 1 + \frac{\bar{c}_e - \bar{c}_u}{\bar{c}_e} \\
\approx 1 + \sigma (E[\log (c_e) - \log (c_u)]) \\
\]
Combining, we have
\[
W^{Social} + 1 \approx (1 + \sigma (E[\log (c_e) - \log (c_u)])) \left( 1 + \sigma \left[ \frac{-\text{dlog}(c_{\text{pre}})}{\text{dp}} - E[\log (c_e) - \log (c_u)] \right] (E[P|U = 1] - E[P|U = 0]) \right) \\
\]
Now, approximating $(1 + x)(1 + y) \approx 1 + x + y$ yields
\[
W^{Social} \approx (1 - (E[P|U = 1] - E[P|U = 0])) \sigma (E[\log (c_e) - \log (c_u)]) + (E[P|U = 1] - E[P|U = 0]) \sigma \frac{-\text{dlog}(c_{\text{pre}})}{\text{dp}} \\
\]
or
\[
W^{Social} \approx (1 - (E[P|U = 1] - E[P|U = 0])) W^{Ex-\text{post}} + (E[P|U = 1] - E[P|U = 0]) W^{Ex-\text{ante}} \\
\]
62
<table>
<thead>
<tr>
<th>Variable</th>
<th>Panel 1: Baseline Sample</th>
<th>Panel 2: Health Sample</th>
<th>Panel 3: Married Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>mean</td>
<td>std dev</td>
<td>mean</td>
</tr>
<tr>
<td><strong>Selected Observables (subset of ( X ))</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>56.1</td>
<td>5.1</td>
<td>56.1</td>
</tr>
<tr>
<td>Male</td>
<td>0.40</td>
<td>0.49</td>
<td>0.41</td>
</tr>
<tr>
<td>Wage</td>
<td>36,057</td>
<td>143,883</td>
<td>37,523</td>
</tr>
<tr>
<td>Job Tenure (Years)</td>
<td>12.7</td>
<td>10.8</td>
<td>12.7</td>
</tr>
<tr>
<td><strong>Unemployment Outcome (( U ))</strong></td>
<td>0.031</td>
<td>0.173</td>
<td>0.032</td>
</tr>
<tr>
<td><strong>Subjective Probability Elicitation (( Z ))</strong></td>
<td>15.7</td>
<td>24.8</td>
<td>15.7</td>
</tr>
<tr>
<td><strong>Spousal Labor Supply</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Working for Pay</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fraction Entering</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td><strong>Sample Size</strong></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of Observations</td>
<td>26,640</td>
<td></td>
<td>22,831</td>
</tr>
<tr>
<td>Number of Households</td>
<td>3,467</td>
<td></td>
<td>3,180</td>
</tr>
</tbody>
</table>

**Notes:** This table presents summary statistics for the samples used in the paper. Panel 1 presents the baseline sample used in Part I of the analysis. Panel 2 presents the statistics for the subset of the baseline sample that have non-zero health variables for the extended controls used in Part I. Panel 3 presents the summary statistics for the sub-sample of respondents married in the both the current and previous wave of the survey whose spouses have non-missing responses to the question of whether they work for pay. The rows present selected summary statistics, including the age of respondents, gender, wage, and job tenure. The unemployment outcome is defined using the subsequent survey wave to construct an indicator for the individual losing his/her job involuntarily in the subsequent 12 months after the baseline survey. The fraction entering variable is defined as an indicator for the spouse not working for pay last wave and working for pay this wave.
### TABLE II

**Lower Bound Estimates**

<table>
<thead>
<tr>
<th>Specification:</th>
<th>Alternative Controls</th>
<th>Sub-Samples</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Baseline (1)</td>
<td>Age &lt;= 55 (4)</td>
</tr>
<tr>
<td></td>
<td>Demo (2)</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Health (3)</td>
<td></td>
</tr>
<tr>
<td>$E[T_{Z}(P_{Z})-1]$</td>
<td>0.7682 (0.053)</td>
<td>0.6983 (0.081)</td>
</tr>
<tr>
<td>s.e.</td>
<td>0.0803 (0.051)</td>
<td>0.8150 (0.066)</td>
</tr>
<tr>
<td>$E[m_{Z}(P_{Z})]$</td>
<td>0.7198 (0.052)</td>
<td>0.6513 (0.058)</td>
</tr>
<tr>
<td>s.e.</td>
<td>0.0236 (0.002)</td>
<td>0.0256 (0.002)</td>
</tr>
<tr>
<td>p-value</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>$Pr{U=1}$</td>
<td>0.0307</td>
<td>0.0297</td>
</tr>
</tbody>
</table>

**Controls**
- **Demographics**: X X X X X X X X X
- **Job Characteristics**: X X X X X X X X X
- **Health**: X

**Num of Obs.** 26640 26640 22831 11134 15506 13320 13320 17681 8959
**Num of HHs** 3467 3467 3180 2255 3231 2916 2259 2939 2447

**Notes:** Table presents estimates of the nonparametric lower bounds on $E[T(P)]$ and the average mean residual risk function, $E[m(P)]$. 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 first row presents estimates of the lower bounds of $E[T(P)]$, which is computed as $1 + E[m(ZP_{Z})]/Pr\{U=1\}$. The value of $E[m_{Z}(P_{Z})]$ is reported in the second row. This is computed using the distribution of predicted values (illustrated in Figure II, Panel A). I construct the average predicted value above a given threshold within an age-by-gender aggregation window; Appendix Table I reports the robustness to alternative aggregation windows. The third row reports the p-value from the test that the coefficients in the probit specification for $Pr\{U|X,Z\}$ are all equal to zero, clustering the standard errors at the household level. All standard errors for $E[T_{Z}(P_{Z})]$ and $E[m_{Z}(P_{Z})]$ are constructed using 500 bootstrap resamples at the household level.
### TABLE III

Minimum Pooled Price Ratio

| Specification | Alternative Controls | Sub-Samples | |
|---------------|-----------------------|-------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|----------------|
| Inf T(p) - 1  | (1) Baseline           | (2) Demo    | (3) Health    | (4) Age <= 55 | (5) Age > 55  | (6) Below Median Wage | (7) Above Median Wage | (8) Tenure > 5 yrs | (9) Tenure <= 5 yrs |
| s.e.          | (0.203)               | (0.655)     | (0.268)       | (0.306)        | (0.279)        | (0.417)        | (0.268)        | (0.392)        | (0.336)        |
| Controls      |                       |             |               | X Demographics | X X            | X              | X              | X              | X X            | X              |
|               |                       |             |               | X Job Characteristics | X X | X | X | X X | X X |
|               |                       |             |               | X Health Characteristics | X X | X | X | X X | X 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 minimum pooled price ratio, $\inf T(p)$. 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 table reports the minimum pooled price ratio across the 3 point masses included in the distribution, excluding the highest value of the point mass (which is mechanically 1). Appendix Table III provides the estimated distribution values. 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.
### TABLE IV
Impact of Unemployment on Consumption and Implied WTP for UI

<table>
<thead>
<tr>
<th>Specification:</th>
<th>Full Sample</th>
<th>Employed in t-1</th>
<th>Controls for Needs</th>
<th>Individual Fixed Effects</th>
<th>Over 40 Sample</th>
<th>With Outliers</th>
<th>Exclude Food Stamps</th>
<th>p10</th>
<th>p90</th>
</tr>
</thead>
<tbody>
<tr>
<td>Panel 1: Reduced Form Impact on $\log(c_{t-1}) - \log(c_t)$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemp</td>
<td>-0.0632***</td>
<td>-0.0761***</td>
<td>-0.0724***</td>
<td>-0.0701***</td>
<td>-0.0599***</td>
<td>-0.0951***</td>
<td>-0.164***</td>
<td>-0.212***</td>
<td>0.0315**</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.00553)</td>
<td>(0.00849)</td>
<td>(0.00886)</td>
<td>(0.0116)</td>
<td>(0.0149)</td>
<td>(0.0120)</td>
<td>(0.0158)</td>
<td>(0.0231)</td>
<td>(0.0133)</td>
</tr>
<tr>
<td>Specification Details</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sample Employed in t-1</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Controls for change in log needs</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individual Fixed Effects</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean Dep Var</td>
<td>0.047</td>
<td>0.048</td>
<td>0.049</td>
<td>0.049</td>
<td>0.030</td>
<td>0.055</td>
<td>0.057</td>
<td>0.048</td>
<td>0.048</td>
</tr>
<tr>
<td>Num of Obs.</td>
<td>88705</td>
<td>81326</td>
<td>67904</td>
<td>67904</td>
<td>30481</td>
<td>84325</td>
<td>82948</td>
<td>81326</td>
<td>81326</td>
</tr>
<tr>
<td>Num of HHs</td>
<td>11964</td>
<td>11290</td>
<td>10469</td>
<td>10469</td>
<td>5529</td>
<td>11441</td>
<td>11230</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Panel 2: First Stage Impact on $P_{\Delta^{t_1}}$

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
<th>(9)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta^{t_1}$ Stage</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>s.e.</td>
<td>0.803***</td>
<td>0.803***</td>
<td>0.803***</td>
<td>0.803***</td>
<td>0.803***</td>
<td>0.803***</td>
<td>0.803***</td>
<td>0.803***</td>
<td>0.803***</td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.012)</td>
<td>(0.012)</td>
<td>(0.012)</td>
<td>(0.012)</td>
<td>(0.012)</td>
<td>(0.012)</td>
<td>(0.012)</td>
<td>(0.012)</td>
</tr>
</tbody>
</table>

Panel 3: Implied Causal Effect on Consumption

<table>
<thead>
<tr>
<th>IV Impact of U on $\log(c_t)$</th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>s.e.</td>
<td>-0.079***</td>
<td>-0.095***</td>
<td>-0.091***</td>
<td>-0.087***</td>
<td>-0.075***</td>
<td>-0.118***</td>
<td>-0.205***</td>
<td>-0.264***</td>
<td>0.039***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.011)</td>
<td>(0.011)</td>
<td>(0.014)</td>
<td>(0.019)</td>
<td>(0.015)</td>
<td>(0.020)</td>
<td>(0.029)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Markup WTP for UI ($\sigma = 2$)</td>
<td>15.8%</td>
<td>18.9%</td>
<td>18.3%</td>
<td>17.4%</td>
<td>14.9%</td>
<td>23.7%</td>
<td>40.9%</td>
<td>52.8%</td>
<td>-7.8%</td>
</tr>
</tbody>
</table>

Notes: This Table presents 2-sample IV estimates of the causal impact of unemployment on consumption, and the implied willingness to pay for UI. Panel 1 reports the coefficients from a regression of the change in log food consumption between years t-1 and t on an indicator of unemployment in year t. The sample includes all household heads in the PSID. Column (1) controls for a cubic in age and year dummies. Column (2) restricts the sample to those who are not unemployed in year t-1. Column (3) adds controls for the change in log expenditure needs (“need_std_p”) between t-1 and t and the change in total household size between t-1 and t. Column (4) adds individual fixed effects to the specification in Column (3). Column (5) restricts the sample to those 40 and over for the specification in Column (3). Following Gruber (1997), Columns (1)-(5) and (8)-(9) drop observations with more than a 3-fold change in consumption and add expenditures from food stamps to food spending in and out of the house; Column (6) includes these outliers following the specification for those who are not unemployed in year t-1. Column (7) uses food expenditures excluding food stamps. Column (8) presents the results from a quantile regression at the 10th quantile for the specification in Column (2). The first row presents the estimated coefficient on the unemployment indicator in year t, along with its standard error. The second row presents the The Private WTP multiplies this by a coefficient of relative risk aversion of 2. Standard errors for the consumption drop equivalent are approximated as the reduced form standard errors scaled by the coefficient on U in the first stage. All standard errors in Columns (1)-(7) are clustered at the household level. The quantile regressions in Columns (8)-(9) present robust standard errors. Panel 2 presents the estimated amount of information revealed between the previous year and the subsequent realization of unemployment. Using the HRS sample, the estimates are constructed using a regression of the subjective probability elicitation, $Z$, on an indicator for subsequent unemployment in the next 12 months, $U$. This provides an estimate of $E[P|U=1] - E[P|U=0]$, and the table reports the value of $E[P|U=1] - E[P|U=0]$. Standard errors are clustered at the household level. Panel 3 reports the implied causal effect of unemployment on log consumption by scaling the estimates in Panel 1 by the estimates in Panel 2. The Private WTP multiplies this by a coefficient of relative risk aversion of 2. Standard errors for the consumption drop equivalent are approximated as the reduced form standard errors scaled by the coefficient on U in the first stage.
TABLE V
Ex-Ante Drop in Food Expenditure Prior to Unemployment and Implied (Ex-Ante) Willingness to Pay for UI

<table>
<thead>
<tr>
<th>Specification:</th>
<th>Full Sample</th>
<th>Employed in t-2 and t-1</th>
<th>Controls for Needs</th>
<th>Individual Fixed Effects</th>
<th>Over 40 Sample</th>
<th>With Outliers</th>
<th>Household Income Controls</th>
<th>Household Head Income Controls</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemp</td>
<td>-0.0336***</td>
<td>-0.0250***</td>
<td>-0.0249**</td>
<td>-0.0231*</td>
<td>-0.0287*</td>
<td>-0.0231*</td>
<td>-0.0259***</td>
<td>-0.0248***</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.00570)</td>
<td>(0.00942)</td>
<td>(0.00994)</td>
<td>(0.0130)</td>
<td>(0.0151)</td>
<td>(0.0121)</td>
<td>(0.00935)</td>
<td>(0.00950)</td>
</tr>
</tbody>
</table>

Specification Details
- Sample Employed in t-2 and t-1: X X X X X X X X
- Controls for change in log needs (t-2 vs t-1): X X X
- Individual Fixed Effects: X
- Change in log HH inc (t-2 vs t-1) (3rd order poly): X
- Change in log HH head inc (t-2 vs t-1) (3rd order poly): X

Mean Dep Var | 0.049 | 0.053 | 0.054 | 0.054 | 0.036 | 0.060 | 0.053 | 0.053 |
Num of Obs.   | 80984 | 70503 | 58987 | 58987 | 27264 | 72758 | 70415 | 69076 |
Num of HHs    | 11055 | 10042 | 8869  | 8869  | 4772  | 10156 | 10033 | 9929 |

Panel 2: Split-Sample IV Welfare Calculation

Δ₁ Mult Stage
- 0.103
- (0.016)

\[ d[log(c_{pot}(p))]/dp \] (2-sample 2SLS)
- 0.33***
- (0.06)

W_{\text{ex-ante}} (σ = 2)
- 0.65***
- (0.11)

Notes: This Table presents the split-sample IV estimates of the impact of \( p \) on log consumption. The sample includes all household heads. Panel 1 reports the coefficients from a regression of the change in log food consumption between years t-2 and t-1 on an indicator of unemployment. Column (1) controls for a cubic in age and year dummies. Column (2) restricts the sample to those who are not unemployed in either t-2 or t-1. Column (3) adds controls for the change in log expenditure needs ("need_std_p") between t-2 and t-1 and the change in total household size between t-2 and t-1. Column (4) adds individual fixed effects to the specification in Column (3). Column (5) restricts the sample to those 40 and over for the specification in Column (3). Following Gruber (1997), Columns (1)-(5) and (7)-(8) drop observations with more than a 3-fold change in consumption; Column (6) includes these outliers following the specification for those who are not unemployed in both t-1 and t-2. Column (7) adds controls to the specification in Column (2) for a third degree polynomial in the household's change in log income between years t-2 and t-1. Column (8) adds controls to the specification in Column (2) for a third degree polynomial in the household head's change in log income between years t-2 and t-1. Panel 2 reports the impact of unemployment on the elicitation. The first row reports the difference in the coefficient from a regression of the elicitation, \( Z \), on subsequent unemployment in the next year, \( U \), and the coefficient from a regression of \( Z \) on an indicator for unemployment in the 12-24 months after the survey. Appendix Table IV provides the baseline regression results for this first stage calculation. The standard error is computed using bootstrap resampling at the household level (500 replications). The consumption drop equivalent reports divides the coefficient in Panel 1 by the coefficient on the regression of the elicitation on unemployment to arrive at the estimate of \( dlog(c)/dp \). The implied WTP multiplies this by a coefficient of relative risk aversion of 2. Standard errors for the consumption drop equivalent are approximated as the reduced form standard errors scaled by the coefficient on \( U \) in the first stage. All standard errors are clustered at the household level.
<table>
<thead>
<tr>
<th>Specification:</th>
<th>Baseline</th>
<th>Sample without Future Job Loss</th>
<th>Full Time Work</th>
<th>2yr Lagged Entry (&quot;Placebo&quot;)</th>
<th>Household Fixed Effects</th>
<th>Individual Fixed Effects</th>
<th>Exit</th>
<th>Spouse Unemployment</th>
</tr>
</thead>
<tbody>
<tr>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
<td>(8)</td>
<td></td>
</tr>
<tr>
<td>Elicitation (Z)</td>
<td>0.0282***</td>
<td>0.0277***</td>
<td>0.0278***</td>
<td>0.00464</td>
<td>0.0263***</td>
<td>0.0290</td>
<td>0.0170</td>
<td>0.0250***</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.00868)</td>
<td>(0.00896)</td>
<td>(0.00975)</td>
<td>(0.00789)</td>
<td>(0.0114)</td>
<td>(0.0181)</td>
<td>(0.0116)</td>
<td>(0.00964)</td>
</tr>
<tr>
<td>Panel 2: Welfare Calculation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Var / Signal Var (var(Z</td>
<td>X)/var(P</td>
<td>X))</td>
<td>11.00</td>
<td>11.00</td>
<td>11.00</td>
<td>18.17</td>
<td>11.00</td>
<td>11.00</td>
</tr>
<tr>
<td>bootstrap s.e.</td>
<td>(1.41)</td>
<td>(1.40)</td>
<td>(1.37)</td>
<td>(3.54)</td>
<td>(1.36)</td>
<td>(1.32)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$W_{cov,X}$ ($\epsilon_{uv} = 0.5$)</td>
<td>0.62***</td>
<td>0.59***</td>
<td>0.63***</td>
<td>0.29</td>
<td>0.59***</td>
<td>0.69**</td>
<td></td>
<td></td>
</tr>
<tr>
<td>bootstrap s.e.</td>
<td>(0.21)</td>
<td>(0.22)</td>
<td>(0.24)</td>
<td>(0.28)</td>
<td>(0.25)</td>
<td>(0.32)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean Dep Var</td>
<td>0.04</td>
<td>0.04</td>
<td>0.05</td>
<td>0.04</td>
<td>0.04</td>
<td>0.04</td>
<td>0.09</td>
<td>0.03</td>
</tr>
<tr>
<td>Num of Obs.</td>
<td>11049</td>
<td>10726</td>
<td>11049</td>
<td>11049</td>
<td>11049</td>
<td>11049</td>
<td>11049</td>
<td>9079</td>
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<tr>
<td>Num of HHs</td>
<td>2214</td>
<td>2194</td>
<td>2214</td>
<td>2214</td>
<td>2214</td>
<td>2214</td>
<td>2214</td>
<td>1359</td>
</tr>
</tbody>
</table>

Notes: This table presents the coefficients from a regression of spousal labor entry on the subjective elicitation. I restrict the sample to respondents who are married in both the current and previous wave. I define spousal entry as an indicator for the event that both (a) the spouse was not working for pay in the previous wave (2 years prior) and (b) the spouse is currently working for pay. For Columns (1)-(7) I include observations for which the spouse was working for pay in the previous wave (these observations are coded as zero). Column (1) presents a linear regression of an indicator for spousal labor entry on the elicitation, Z, and controls for age, age squared, gender, log wage, year, and census division (10 regions), and an indicator for Z=0 to deal with potential non-linearities resulting from focal point responses. Column (2) drops the indicator for Z=0. Column (3) restricts to the subsample that does not lose their job in the subsequent 12 months. Column (4) defines spousal labor force entry using only full time employment. I define an indicator for the event that both (a) the spouse was not employed full time in the previous wave and (b) is currently working full time. Column (5) uses the lagged value of Z from the previous wave (2 years prior) as a “placebo” test. Note this is not an exact placebo test to the extent to which the information is correlated across time. Column (6) adds household fixed effects to the specification in Column (1). Column (7) adds individual fixed effects to the specification in Column (1). Column (8) replaces the dependent variable with an indicator for exit of the spouse from the labor market. I define exit as an indicator for being in the labor force last wave (2 years prior) and out of the labor force this wave. Column (9) replaces the dependent variable with an indicator for spouse unemployment in the subsequent 12 months and restricts the sample to spouses currently in the labor market.

Panel 2 presents the welfare implications of each model. I scale the regression coefficient in Panel 1 by the total variance of Z relative to the signal variance (var(P)). I estimate the variance of Z given X by regressing Z on the control variables and squaring the RMSE. I estimate the variance of P given X as follows. I regress the future unemployment indicator, U, on the controls and take the residuals. I regress Z on the controls and take those residuals. I then construct the covariance between these two residuals and rescale by (n-1)/(n-df), where df is the number of degrees of freedom in the regression of U on the controls. This provides an estimate of Cov(Z,L|X), which is an approximation to var(P|X) that is exact under classical measurement error. The implied WTP is constructed by taking the regression coefficient, multiplying by the total variance / signal variance, and dividing by the semi-elasticity of spousal labor supply, here assumed to be 0.5. For example, the 0.6 in Column (1) is obtained by 0.0273 * 11 / 0.5 = 0.60. All standard errors in Panel 2 are constructed using 500 bootstrap repetitions, resampling at the household level.
TABLE VII
Social Willingness to Pay for Unemployment Insurance

<table>
<thead>
<tr>
<th>Ex-ante Method:</th>
<th>Ex-Ante Consumption Drop</th>
<th>Ex-Ante Spousal Labor Supply</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Social WTP, $W_{social}$</td>
<td>0.248</td>
<td>0.124</td>
</tr>
<tr>
<td>Insurance against $p$, $W_{ex-ante}$</td>
<td>0.485</td>
<td>0.242</td>
</tr>
<tr>
<td>Weight, $E[P</td>
<td>U=1] - E[P</td>
<td>U=0]$</td>
</tr>
<tr>
<td>Insurance against $U$ (given $p$), $W_{ex-post}$</td>
<td>0.189</td>
<td>0.095</td>
</tr>
<tr>
<td>Weight, $1 - (E[P</td>
<td>U=1] - E[P</td>
<td>U=0])$</td>
</tr>
</tbody>
</table>

**Specification Details**

<table>
<thead>
<tr>
<th>Coeff. Of Relative Risk Aversion, $\sigma$</th>
<th>Spousal Labor Supply Semi-Elasticity, $\varepsilon_{semi}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>2</td>
<td>N/A</td>
</tr>
<tr>
<td>1</td>
<td>N/A</td>
</tr>
<tr>
<td>3</td>
<td>N/A</td>
</tr>
<tr>
<td>2</td>
<td>0.50</td>
</tr>
<tr>
<td>2</td>
<td>0.25</td>
</tr>
<tr>
<td>2</td>
<td>0.75</td>
</tr>
<tr>
<td>1</td>
<td>0.50</td>
</tr>
<tr>
<td>3</td>
<td>0.50</td>
</tr>
</tbody>
</table>

Notes: This Table presents the social willingness to pay for unemployment insurance as a weighted average of the ex-ante and ex-post willingnesses to pay outlined in Tables IV, V, and VI, using weights outlined in Table IV, Panel 2. All specifications use the baseline specification in Column (2), Table IV, for the ex-post willingness to pay using the impact of unemployment on consumption. The columns differ in the coefficients used to translate behavioral responses into willingnesses to pay ($\sigma$ and $\varepsilon_{semi}$) and the method used to calculate the ex-ante insurance value (consumption response versus spousal labor supply response). Columns (1)-(3) use the ex-ante consumption drop in Column (2), Table VI to value insurance under different assumptions for risk aversion. Columns (4)-(7) use the spousal labor supply response in Table V, Column (1), to measure the ex-ante insurance value, and provide a range of estimates for various labor supply semi-elasticities and coefficients of relative risk aversion (which continues to affect the value of insurance against $U$ given $p$).
### APPENDIX TABLE I

Alternative Lower Bound Specifications

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td>$E[T_4(P_Z)-1]$</td>
<td>0.7687</td>
<td>0.6802</td>
<td>0.7716</td>
<td>0.7058</td>
<td>0.7150</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.058)</td>
<td>(0.051)</td>
<td>(0.05)</td>
<td>(0.048)</td>
<td>(0.048)</td>
</tr>
<tr>
<td>$E[m_Z(P_Z)]$</td>
<td>0.0239</td>
<td>0.0209</td>
<td>0.0237</td>
<td>0.0217</td>
<td>0.0220</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>p-value</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
</tr>
<tr>
<td>$Pr[U=1]$</td>
<td>0.0310</td>
<td>0.0307</td>
<td>0.0307</td>
<td>0.0307</td>
<td>0.0307</td>
</tr>
</tbody>
</table>

**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.

<table>
<thead>
<tr>
<th>Controls</th>
<th>Demographics</th>
<th>Job Characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>X</td>
<td>X</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Elicitation Specification</th>
<th>Polynomial Degree</th>
<th>Focal pt dummies (0, 50, 100)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>3</td>
<td>X</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Aggregation Window</th>
<th>Age x Gender</th>
<th>Age x Gender</th>
<th>Constant</th>
<th>Age x Gender</th>
<th>Age x Gender</th>
<th>Age x Gender</th>
<th>Age x Gender</th>
<th>Age x Gender</th>
<th>Age x Gender</th>
<th>Age x Gender</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemployment Outcome Window</td>
<td>12 months</td>
<td>12 months</td>
<td>12 months</td>
<td>12 months</td>
<td>12 months</td>
<td>12 months</td>
<td>12 months</td>
<td>24 months</td>
<td>6-24 months</td>
<td>6-12 months</td>
</tr>
<tr>
<td>Error Specification</td>
<td>Probit</td>
<td>Probit</td>
<td>Probit</td>
<td>Probit</td>
<td>Probit</td>
<td>Probit</td>
<td>Probit</td>
<td>Probit</td>
<td>Probit</td>
<td>Probit</td>
</tr>
</tbody>
</table>

| 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  |
APPENDIX TABLE II
Estimation of F(p|X)

<table>
<thead>
<tr>
<th>Specification</th>
<th>Alternative Controls</th>
<th>Sub-Samples</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Baseline</td>
<td>Demo</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>1st mass</td>
<td>Location</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>s.e.</td>
<td>(0.001)</td>
</tr>
<tr>
<td></td>
<td>Weight</td>
<td>0.446</td>
</tr>
<tr>
<td></td>
<td>s.e.</td>
<td>(0.024)</td>
</tr>
<tr>
<td></td>
<td>T(p)</td>
<td>63.839</td>
</tr>
<tr>
<td></td>
<td>s.e.</td>
<td>6.1E+06</td>
</tr>
<tr>
<td>2nd mass</td>
<td>Location</td>
<td>0.031</td>
</tr>
<tr>
<td></td>
<td>s.e.</td>
<td>N/A</td>
</tr>
<tr>
<td></td>
<td>Weight</td>
<td>0.471</td>
</tr>
<tr>
<td></td>
<td>s.e.</td>
<td>(0.024)</td>
</tr>
<tr>
<td></td>
<td>T(p)</td>
<td>4.360</td>
</tr>
<tr>
<td></td>
<td>s.e.</td>
<td>0.203</td>
</tr>
<tr>
<td>3rd Mass</td>
<td>Location</td>
<td>0.641</td>
</tr>
<tr>
<td></td>
<td>s.e.</td>
<td>(0.004)</td>
</tr>
<tr>
<td></td>
<td>Weight</td>
<td>0.082</td>
</tr>
<tr>
<td></td>
<td>s.e.</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Controls</td>
<td>Demographics</td>
<td>X</td>
</tr>
<tr>
<td></td>
<td>Job Characteristics</td>
<td>X</td>
</tr>
<tr>
<td></td>
<td>Health Characteristics</td>
<td>X</td>
</tr>
<tr>
<td>Num of Obs.</td>
<td>26,640</td>
<td>26,640</td>
</tr>
<tr>
<td>Num of HHs</td>
<td>3,467</td>
<td>3,467</td>
</tr>
</tbody>
</table>

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|X) 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)

<table>
<thead>
<tr>
<th>Variable</th>
<th>mean</th>
<th>std dev</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>39.794</td>
<td>10.27</td>
</tr>
<tr>
<td>Male</td>
<td>0.808</td>
<td>0.39</td>
</tr>
<tr>
<td>Unemployment</td>
<td>0.059</td>
<td>0.24</td>
</tr>
<tr>
<td>Year</td>
<td>1985</td>
<td>7.62</td>
</tr>
<tr>
<td>Log Consumption</td>
<td>8.199</td>
<td>0.65</td>
</tr>
<tr>
<td>Log Expenditure Needs</td>
<td>8.124</td>
<td>0.32</td>
</tr>
<tr>
<td>Consumption growth (log(c_{t-2})-log(c_{t-1}))</td>
<td>0.049</td>
<td>0.360</td>
</tr>
</tbody>
</table>

Sample Size

<p>| | |</p>
<table>
<thead>
<tr>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Number of Observations</td>
<td>80,984</td>
</tr>
<tr>
<td>Number of Households</td>
<td>11,055</td>
</tr>
</tbody>
</table>

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.
<table>
<thead>
<tr>
<th>Specification:</th>
<th>Baseline</th>
<th>HH Cons</th>
<th>Sample Z &gt; 0</th>
<th>Sample U = 0</th>
<th>Non-Durable Consumption</th>
<th>No Controls</th>
<th>No 1{Z=0} Control</th>
</tr>
</thead>
<tbody>
<tr>
<td>Elicitation (Z)</td>
<td>-0.160**</td>
<td>-0.110*</td>
<td>-0.171**</td>
<td>-0.162**</td>
<td>-0.162**</td>
<td>-0.345***</td>
<td>-0.0401</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.0781)</td>
<td>(0.0596)</td>
<td>(0.0777)</td>
<td>(0.0783)</td>
<td>(0.0789)</td>
<td>(0.0798)</td>
<td>(0.0659)</td>
</tr>
<tr>
<td>Elicitation * Unemp (Z*U)</td>
<td>-0.137</td>
<td>-0.421**</td>
<td>-0.0771</td>
<td>-0.257</td>
<td>-0.0000475</td>
<td>-0.460**</td>
<td></td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.268)</td>
<td>(0.207)</td>
<td>(0.268)</td>
<td>(0.303)</td>
<td>(0.296)</td>
<td>(0.218)</td>
<td></td>
</tr>
<tr>
<td>Elicitation of 0 (1{Z=0})</td>
<td>-0.0893***</td>
<td>-0.0587**</td>
<td>-0.0904***</td>
<td>-0.120***</td>
<td>-0.160***</td>
<td></td>
<td></td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.0334)</td>
<td>(0.0279)</td>
<td>(0.0334)</td>
<td>(0.0356)</td>
<td>(0.0365)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Elicitation of 0 * Unemp (1{Z=0}*U)</td>
<td>0.338</td>
<td>0.161</td>
<td>0.307</td>
<td>0.191</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.222)</td>
<td>(0.180)</td>
<td>(0.220)</td>
<td>(0.239)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemp (U)</td>
<td>-0.0845</td>
<td>0.0862</td>
<td>-0.120</td>
<td>-0.0936</td>
<td>-0.181</td>
<td>0.118</td>
<td></td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.165)</td>
<td>(0.128)</td>
<td>(0.164)</td>
<td>(0.164)</td>
<td>(0.187)</td>
<td>(0.120)</td>
<td></td>
</tr>
</tbody>
</table>

Num of Obs. | 2,798 | 2,798 | 1,503 | 2,696 | 2,798 | 2,798 | 2,798 |
Num of HHs | 862 | 862 | 579 | 843 | 862 | 862 | 862 |

Notes: This table presents estimates from a regression of log consumption expenditure on subjective elicitions of becoming unemployed and indicators of the event of actually becoming unemployed in the subsequent 12 months. Consumption expenditure is measured 12 months after the subjective probability elicitation, and asks about consumption expenditure covering the previous 12 months. Columns (1) and (3)-(7) use log household consumption per capita as the dependent variable, taking the household consumption expenditure and dividing it by the total number of household members before taking the log. Column (2) uses log household consumption. Column (1) reports the baseline results for a specification that includes the elicitation, Z, an indicator for Z=0 to capture the nonlinearity in Figure IV, an indicator for subsequent unemployment, U, an interaction of the elicitation with the indicator for unemployment, and an interaction of an indicator for Z=0 with the indicator for future unemployment, U. Column (2) replicates Column (1) with household consumption as the dependent variable. Column (3) restricts the sample to those with positive elicitation. Column (4) restricts the sample to those who do not become unemployed in the subsequent 12 months (U=0). Column (5) replicates the specification in Column (1) using non-durable consumption per capita instead of total consumption. Column (6) drops all control variables for age, gender, log wage, year, and region. Column (7) considers the specification in Column (1) but drops the indicators for focal point responses at Z=0.
### Appendix Table V

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

<table>
<thead>
<tr>
<th>Dependent Variable:</th>
<th>Coeff. on Z (1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Unemp (Next 12 months)</td>
<td>0.197***</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.0123)</td>
</tr>
<tr>
<td>Unemp (12-24 months)</td>
<td>0.0937***</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.0113)</td>
</tr>
<tr>
<td>Difference</td>
<td>0.1031***</td>
</tr>
<tr>
<td>bootstrap s.e.</td>
<td>(0.0159)</td>
</tr>
<tr>
<td>Num of Obs.</td>
<td>26,640</td>
</tr>
</tbody>
</table>

Note: This table presents estimates from two separate regressions of the elicitation on unemployment in the subsequent 12 months (U) and the elicitation, Z, on unemployment in the 12-24 months after the elicitation. The standard error for the difference is computed using 500 bootstrap repetitions resampling at the household level.
FIGURE I: Histogram of Subjective Probability Elicitations

Notes: This figure presents a histogram of responses to the question “What is the percent chance (0-100) that you will lose your job in the next 12 months?” The figure reports the histogram of responses for the baseline sample outlined in Panel 1 of Table I. As noted in previous literature, responses tend to concentrate on focal point values, especially $Z = 0$. 
Notes: These figures present the predictive content in the subjective probability elicitation. Panel A reports the mean unemployment rate in each elicitation category controlling for demographic and job characteristics. To construct this figure, I first regress the unemployment indicator on the demographic and job characteristics and take the residuals. I then construct the mean of these residuals in each of the elicitation categories and add back the mean unemployment rate. To obtain the 5% / 95% confidence intervals, I run a regression of unemployment on each of these categories with zero as the omitted category, clustering the standard errors by household. Panel B reports the kernel density of the distribution of predicted values from a regression of both observables and the elicitation on $U$, $Pr(U|X, Z)$, minus the predicted values from a regression of $U$ on observables, $X$, $Pr(U|X)$. Under the Assumptions outlined in the text, the true distribution of $P$ given $X$ is a mean-preserving spread of this distribution of predicted values.
Notes: These figures present estimates of the lower bounds on the average pooled price ratio, $E[T_Z(P_Z)]$, using a range of sub-samples and controls. Panel A reports estimates of $E[T_Z(P_Z)]$ for a range of control variables. Panel B adds a specification with individual fixed effects to Panel A and relies on a linear specification as opposed to a probit (see Appendix Table I, Column (2) for the baseline estimation using the linear model). The horizontal axis presents the Psuedo-$R^2$ of the specification for $Pr\{U|X,Z\}$. Panel C constructs separate estimates by industry classification. Panel D constructs estimates by age group. Panel E constructs separate estimates for each wave of the survey. Panel F restricts the sample to varying sub-samples, analyzing the relationship between $E[T_Z(P_Z)]$ and restrictions to lower-risk subsamples. The horizontal axis in Panels C-F report the mean unemployment probability, $Pr\{U\}$, for each sub-sample.
Notes: The figure present coefficients from a regression of an indicator for a spouse entering the labor force – defined as an indicator for not working in the previous wave and working in the current wave – on category indicators for the subjective probability elicitations, $Z$, controlling for realized unemployment status, $U$, and several observable characteristics: age, age squared, gender, year dummies, census division, log wage, and an indicator for being married.
FIGURE V: Impact of Unemployment on Consumption Growth

A. Full Sample

B. No Unemployment in \( t - 1 \) or \( t - 2 \)

Notes: These figures present coefficients from separate regressions of leads and lags of the log change in food expenditure on an indicator of unemployment, along with controls for year indicators and a cubic in age. Sample is restricted to household heads. Food expenditure is the sum of food in the home, food outside the home, and food stamps. Following Gruber (1997) and Chetty et al. (2005), I define food stamps by taking the monthly measure and multiplying by 12 for the years where the monthly food stamp measure is available. The horizontal axis presents the years of the lead/lag for the consumption expenditure growth measurement (i.e. 0 corresponds to consumption growth in the year of the unemployment measurement relative to the year prior to the unemployment measurement). Panel A presents the results for the full sample. Panel B restricts the sample to household heads who are not unemployed in \( t - 1 \) or \( t - 2 \).
Notes: This figure presents additional estimates of the lower bound on the average pooled price ratio, \( E[TZ(PZ)] \). 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 \( E[TZ(PZ)] \) 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.
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. Figure reports the confidence interval and the 5 / 95% confidence interval for each estimate in each sample.
Notes: These figures present coefficients from a regression of log household consumption per capita (Panel A) and log total household consumption (Panel B) on category indicators for the subjective probability elicitations, $Z$, controlling for realized unemployment status, $U$, and several observable characteristics: age, age squared, gender, year dummies, census division, log wage, and an indicator for being married.
Notes: These figures present coefficients from a regression of leads and lags of log per capita consumption (Panels A and B) and log household consumption (Panels C and D) on the subjective probability elicitation, controlling for an indicator for realized unemployment, an indicator for a subjective probability elicitation of $Z = 0$, and several observable characteristics: age, age squared, gender, year dummies, census division, log wage, and an indicator for being married. Panels A and C include all observations; Panels B and D restrict the sample to those with positive elicitation, $Z > 0$. The vertical dotted line corresponds to the time of the subjective probability elicitation. The horizontal axis corresponds to the time of the consumption measurement (which includes a 12 month look-back window).
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 (occurring every 2 years). I then use the data on when the job loss occurred 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.
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 V (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 \( t - 2 \).