Knowledge of Future Job Loss and Implications for Unemployment Insurance

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Abstract

This paper provides evidence that individuals’ knowledge about their potential future job loss prevents the existence of a private market for unemployment insurance (UI). Using information contained in subjective probability elicitations, I show privately-traded UI policies would be too adversely selected to be profitable, at any price. Moreover, in response to learning about future unemployment, individuals decrease consumption and spouses are more likely to enter the labor market. From a normative perspective, this suggests existing estimates miss roughly 35% of the social value of UI because it also partially insures against the risk of learning one might lose their job.

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

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

260% 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).

3Two 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, and it has been criticized for shrouding the true price by not saliently noting that the government provides the baseline 30-40% replacement rate (e.g. http://www.mlive.com/jobs/index.ssf/2011/08/get_out_your_calculator_before_you_buy_p.html#).
The government is heavily involved in providing unemployment insurance (UI) benefits, and there is a large literature characterizing the optimal amount of these benefits. Yet there is little empirical literature identifying the market failures (if any) that provide a rationale for this government intervention (Chetty and Finkelstein (2013)). If additional UI increases welfare, why can’t private firms provide this insurance? If there is a microfoundation for the absence of a private market, does this microfoundation change the way one should think about the optimal provision of government 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. This provides a potential rationale for government intervention that requires workers to pay into a government UI system. Moreover, it also suggests previous normative calculations understate the social value of UI. This is because UI insures not only against the risk of job loss conditional on what people know today; but it also provides partial insurance against the risk of learning today that one might lose their job tomorrow.

I begin by developing a model of unemployment risk that characterizes when a private market for UI can exist. Individuals may have private information about their future unemployment prospects (adverse selection), and insurance may increase their likelihood of unemployment (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 probabilities of unemployment adversely selecting their contract.

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 an approach developed in Hendren (2013). 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, individuals hold a significant amount of private information that is not captured by the large set of observable characteristics available in the HRS. The

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4 See, for example, Baily (1976); Gruber (1997); Chetty (2008); Landais (2015).

5 This generalizes the no-trade condition of Hendren (2013) 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.
distribution of predicted values of unemployment generated by the elicitations yield a nonparametric lower bound of 70% on the average markup individuals would have to be willing to pay to cover the cost of higher risks adversely selecting their contract. 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. Additional parametric assumptions on the distribution measurement error in elicitations facilitate estimation of point estimates, which suggest individuals would need to pay markups in excess of 300% in order to create a profitable private UI 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 the markup individuals are willing to pay for UI (Baily (1976); Gruber (1997)). I replicate the finding that unemployment leads to roughly 6-10% lower yearly consumption growth. However, in the year prior to unemployment, consumption growth declines by 2.3% – even on a sample who remain employed (and who experience no income changes). This suggests that first-difference estimates of the impact of unemployment on consumption growth under-state the causal effect of unemployment on consumption, introducing a downward bias in the estimated willingness to pay for UI.

I provide conditions under which one can use a 2-sample IV strategy to recover the causal effect by scaling the impact on consumption growth by the amount of information revealed in the year before the unemployment measurement. Twenty percent of the information about future unemployment is revealed one year prior to unemployment. Scaling the first difference estimate by the remaining eighty percent, $1/0.8 = 1.25$, yields an estimate of the causal effect of unemployment on consumption of 7-12%. Assuming a coefficient of relative risk aversion of 2, this suggests individuals are willing to pay a 20% markup for additional unemployment insurance – well below the 300% markup required to overcome adverse selection. In this sense, private information provides a micro-foundation for the non-existence of a private UI market.\footnote{To be specific, this explains why a private market does not exist for additional insurance on top of all existing other forms of insurance against unemployment, such as savings, informal transfers from family and friends, severance, and government UI benefits. I also discuss why the evidence on how the consumption drop varies with government benefits (e.g. from Gruber (1997)) suggests a private market would not arise even if the government reduced or eliminated its UI benefits.}

Using the same model that micro-founds the absence of the private UI market, I characterize the level of UI benefits that maximizes a utilitarian (ex-ante welfare) criterion. This yields a modified Baily-Chetty condition that suggests UI has value not only as insurance against the realization of unemployment, but also against the ex-ante realization of information about future unemployment.\footnote{This value arises with standard expected-utility (vNM) preferences and is distinct from any non-vNM preference for early realization of information.} I develop two methods to measure this ex-ante value of UI that use consumption responses and
spousal labor supply responses.

For the consumption approach, I exploit the 2.3% consumption drop in the year prior to the unemployment measurement. Following a two-sample IV strategy, I scale the 2.3% consumption drop in the year $t - 1$ relative to $t - 2$ by the amount of information about unemployment revealed over year $t - 1$ relative to $t - 2$. 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 $t - 2$. This suggests fully learning about unemployment would lead to a 23% ex-ante consumption drop prior to becoming unemployed. Scaling by a coefficient of relative risk aversion of 2, this approach suggests individuals are ex-ante willing to pay a 45% markup for insurance against learning they might lose their job.

I also provide a complementary strategy to identify the ex-ante value of insurance that exploits the response of individuals who learn their spouses may lose their job. I show that a 10pp increase in the probability of becoming unemployed in the next year increases spousal labor force participation 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. While estimates for this elasticity are scarce, a semi-elasticity of 0.5 (as used in Kleven et al. (2009)) suggests individuals would be willing to pay a 60% markup to obtain insurance against learning they might lose their job.

Overall, the size of the ex-ante responses of consumption and labor supply suggest individuals obtain significant value from UI not only as insurance against unemployment but also against insurance against the risk that they might lose their job. The empirical estimates suggest this ex-ante component – that is omitted in previous literature (e.g. Gruber (1997)) – comprises more than 35% of the total value of UI.

**Related literature**  This paper is related to a growing 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 elicitation in the HRS are predictive about future unemployment status.

In contrast to many previous approaches, the approaches developed here build upon Hendren (2013) by estimating theoretically-motivated properties of beliefs while simultaneously allowing the

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8In 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). See also Bach (1998) for one of the only papers documenting adverse selection in a UI context in which mortgage insurance companies provide mortgage payments in the event of job loss.
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. This paper is not the first to study the impact of unemployment on consumption or the ex-ante response of consumption or spousal labor supply to future income or unemployment shocks. The contribution of this paper is to provide methods to recover the underlying causal effects of unemployment using subjective belief data and to illustrate how these responses affect the normative valuation of UI benefits. When individuals respond ex-ante, part of the value of insurance is to insure against the need to take these ex-ante responses.

Finally, 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. Previous literature often tests for private information by asking whether existing 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. Combining with the evidence in Hendren (2013) that private information prevents the existence of health-related insurance markets for those with pre-existing conditions, the results suggest a broader pattern that the frictions imposed by private information form the boundary to the existence of insurance markets.

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 based on the impact of unemployment on consumption, and argues it falls short of the willingness to pay that would be required to deliver a profitable private UI market. Section 6 characterizes the socially optimal level of benefits, which illustrates the value of UI as insurance against learning one might lose their job. Section 7 quantifies the ex-ante value of UI using the ex-ante response of consumption and spousal labor supply. Section 8 concludes.

For example, see Guiso et al. (1992); Dynan (1993); Hubbard et al. (1994); Carroll and Sanwick (1997, 1998); Carroll et al. (2003); Lusardi (1997, 1998); Engen and Gruber (2001); Guariglia and Kim (2004); Bloemen and Stancanelli (2005); Barceló and Villanueva (2010); Campos and Reggio (2015); Brown and Matsa (2015). Most closely, Basten et al. (2012) and Gallen (2013) find evidence of ex-ante savings increases in response to future unemployment in Norway and Denmark; Stephens (2001); Stephens Jr (2002) finds evidence of ex-ante consumption drops in the U.S. using the PSID.

Alternative approaches to identifying under-insurance studies the joint distribution of consumption and income (e.g. Meghir and Pistaferri (2011) and Kinnan et al. (2011)).
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 optimal (utilitarian) level of social insurance. For brevity, many of the formal theoretical arguments are provided in the Appendix.

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

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

(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.\(^{11}\)

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.\(^{12}\)

\(^{11}\)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.

\(^{12}\)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 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. More generally, one can micro-found a wide class of models into equation (1), such as a case when $p$ is the outcome of a reservation wage decision.
**No Trade Condition**  When can a private market profitably sell insurance? To answer this, it is useful to begin by making an additional assumption that there is no heterogeneity in the population other than individual’s choices of $p$.\(^{13}\) Then, define $P$ denote the random variable of the choices of $p$ in the status quo world without any additional insurance, $b = \tau = 0$. Suppose an insurer tries to sell an insurance policy that pays $1 in the event of unemployment. If the price is set such that a type $p$ is indifferent to purchasing the insurance, all risks $P \geq p$ would also prefer the policy. Hence, whether or not the insurer makes a profit depends on whether or not the individual of type $p$ is willing to pay the pooled cost of higher risks, $E \left[ P | P \geq p \right]$. Appendix A shows that if no type $p$ is willing to pay this pooled cost of worse risks, there can be no profitable way in which insurers could sell insurance – their policies would be too adversely selected to deliver a positive profit at any price.

Mathematically, Appendix A shows that no trade can occur whenever

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

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

**Moral Hazard versus Adverse Selection**  Although the no trade condition in equation (2) is similar to that of Hendren (2013), a key distinction is that the model allows for the probability of unemployment, $p$, to be a choice of the individual in response to insurance. A priori, one could have imagined that either moral hazard or adverse selection could prevent the existence of a UI market. Perhaps surprisingly, the responsiveness of behavior to insurance does not enter into equation (2). For the first dollar of insurance, the moral hazard cost to the insurer is zero. Although behavior may change, the behavioral response to a small amount of insurance will be small; and the impact

\(^{13}\)Assumption A1 in Appendix A states this formally.
of the small response on the cost of a small insurance policy is second-order – analogous to the logic that the deadweight loss of a tax varies with the square of the tax rate. This insight, initially noted by Shavell (1979), suggests moral hazard does not affect whether insurers’ first dollar of insurance is profitable. In this sense, moral hazard can limit the size of the gains to trade, but does not provide a singular theoretical explanation for the absence of a market. In contrast, the first dollar of insurance can be adversely selected by strictly worse risks, so that private information can explain the absence of a market.

Multi-dimensional Heterogeneity and Other Extensions  For simplicity, the remainder of the paper will operate under the simplification offered by unidimensional heterogeneity. However, the role of the pooled price ratio in characterizing when trade can occur extends to the case of multi-dimensional heterogeneity.\footnote{Multi-dimensional heterogeneity could arise for many reasons. In the current model structure, it arises because different individuals may have differences in the consumption impact of unemployment, $c_e(\theta)$ and $c_u(\theta)$ conditional on $p(\theta)$; but more generally $\frac{u'}{w'}$ could vary conditional on $p(\theta)$ for many reasons including heterogeneous risk aversion and even heterogeneously biased beliefs. To see how one can incorporate biased beliefs, let $S_\theta(p)$ denote an individual of type $\theta$’s belief that $U$ will occur and let $p$ continue to be the true probability $U$ will occur. In this case, $\frac{u'}{w'}$ can be replaced with $\frac{u'(c_u(S_\theta(p)))}{w'(c_e(S_\theta(p)))}$, where $1 - p \frac{S_u(p)}{1 - S_u(p)} u'$ captures the impact of biased beliefs on willingness to pay. Biased beliefs can simply be thought of as another reason individuals are (or are not) willing to pay for insurance, and the pooled price ratio using the true beliefs, $p$, remains the fundamental friction imposed by the presence of private information.} The issue that arises is that there may be two types that have different willingnesses to pay, $\frac{u'(c_u(\theta))}{w'(c_e(\theta))}$, but the same probability of unemployment, $p(\theta)$. Appendix A.1 shows that in general there will exist a mapping, $f(p)$, from a subset of $[0,1]$ into the type space, $\Theta$, such that the no trade condition reduces to testing

$$\frac{u'(c_u(f(p)))}{w'(c_e(f(p)))} \leq T(p) \quad \forall p \quad (3)$$

Even in the presence of multi-dimensional heterogeneity, the pooled price ratio, $T(p)$, continues to be a key measure for the frictions imposed by private information.

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. It shows that plausible regularity conditions imply that the results from Hendren (2013) apply to this setting and suggest that when the no trade condition holds, pooling delivers weakly higher profit than a separating contract. Hence, the no trade condition in (2) also implies menus of contracts will not be profitable. In short, the existence of insurance markets requires someone to be willing to pay the pooled cost of worse risks in order to obtain some insurance.
Empirical Approach  Equation (2) provides a theory of how private information can prevent the existence of a UI market. The next few sections focus on estimating properties of the demand for UI, \( \frac{u'(c_u(p))}{u'(c_e(p))} \), and the pooled price ratio, \( T(p) \).

The empirical analysis will focus on a couple measures of \( T(p) \): the minimum pooled price ratio, \( \inf_T(p) \), and the average pooled price ratio, \( E[T(P)] \). Note that the no trade condition in equation (2) must hold for all \( p \). Absent particular knowledge of how the willingness to pay for UI varies across \( p \), the minimum pooled price ratio provides a natural characterization of how much individuals would have to be willing to pay in order for a profitable market to exist.\(^{15}\)

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 insurance (e.g. because there is no market from which to learn the distribution of types), Appendix A.4 shows that the average pooled price ratio, \( E[T(P)] \), can be the relevant measure for whether a firm can profitably sell insurance on average with a simple random pricing rule. This motivates the average pooled price ratio as a complementary statistic for studying the degree of potential adverse selection in addition to the minimum pooled price ratio. Moreover, an added advantage of the average pooled price ratio – as will be shown in Section 4 – is that one can construct lower bounds on \( E[T(p)] \) under weaker assumptions than are required to estimate the minimum pooled price ratio, \( \inf_T(p) \).

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 over 55 and their spouses (included regardless of age).\(^{16}\)

\(^{15}\)Although not a necessary condition, the no trade condition will hold if

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\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.

\(^{16}\)Despite its focus on an older set of cohorts, the HRS is a natural dataset choice because it contains subjective probability elicitations about future job loss, information on future job loss and unemployment, and a wide range of observable characteristics insurers might use in other markets to price policies. The analysis below will explore how
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? Let $Z$ denote these free-response elicitations. Figure I presents the histogram of the elicitations. As has been noted in previous literature (Gan et al. (2005)), they 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 contrasts with both common sense and observed behavior. As a result, at no point will these elicitations be used as true measures of individuals beliefs (i.e. $Z \neq P$). Instead, Section 4 builds on the approach of Hendren (2013) which uses these elicitations as noisy and potentially biased measures of true beliefs to identify and quantify private information.

**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). For the baseline analysis, 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.

I also consider robustness analyses to other definitions of job loss. For example, 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).

There is also 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 an outcome that is the product of indicators of job loss and an indicator for receiving positive government unemployment insurance benefits in between survey waves. This...
effectively restricts 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.

**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 (2013)) 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.\(^{17}\)

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.\(^{18}\) Changing the set of observable characteristics simulates how the potential for adverse selection varies with the underwriting strategy of the potential insurer. While in principle the results could vary dramatically depending on the types of information included in the observable characteristics, in practice the results will turn out to be fairly stable. This is not because these observables do not predict unemployment, but rather because the frictions imposed by private information are due to a thick upper tail of individuals with high subjective probabilities that does not seem to be affected by the inclusion of additional control variables, as will be discussed below.

**Samples** The sample begins with everyone under 65 currently holding a job who is asked the subjective probability elicitation question, \(Z\). Individuals are excluded if they have missing job loss responses in the subsequent wave, \(U\), or if they have missing observable characteristics, \(X\). The self-employed and those employed in the military are also excluded.

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.\(^{19}\) Mean yearly wages are around $36,000 in the baseline

\(^{17}\)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.

\(^{18}\)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. 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.

\(^{19}\)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.
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 elicitations on average. This is arguably a well-known artifact of the non-classical measurement error process inherent in subjective elicitations. Elicitations are naturally bounded between 0 and 1. Hence, for low probability events, there is a natural tendency for measurement error in elicitations to lead to an upward bias in elicitations. This provides further rationale for treating these elicitations 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 follow previous literature by exploiting the impact of unemployment on food expenditure in the Panel Study of Income Dynamics (PSID) (Gruber (1997); Chetty and Szeidl (2007)). While the HRS provides subjective probability elicitations, it does not provide sufficient data on consumption patterns. I utilize a 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 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.

For the unemployment indicator, I use the measure of current unemployment/employment status at the time of the survey. Because the food expenditure questions ask about how much spending is typical in the household, this timing of employment measure will more accurately create a comparison between the employed and unemployed. However, this definition differs from the job loss definition used in the HRS analysis. Therefore, I replicate the results using a measure of job loss defined as an indicator for being laid off or fired from the job held in the previous wave of the survey.

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20 The baseline results utilizes food expenditure, as this is in the yearly survey through 1997. Post 1997, the PSID asks a broader set of consumption expenditure questions, but is asked only every two years. As a result, the timeline of the survey prevents its direct use in valuing the insurance products discussed below, but Online Appendix Figure VI replicates the baseline results using the 2-year intervals and aggregated consumption expenditure measure.

21 Consumption questions are asked on a 10% sub-sample in a follow-up survey (that is not asked at the same time the elicitations are provided).

22 To compute food stamp expenditure, I follow previous literature and use the response to the monthly food stamp amount multiplied by 12. One potential concern is the differential recall bias in the food stamp questions relative to the food expenditure variables – an issue which I discuss below.
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 81% male. For comparison to the HRS sample, I also present results for older sub-samples. Roughly 5.7% of the sample is unemployed at the time of the survey, and the average nominal consumption growth is 0.049.\footnote{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 unemployment, $U$, 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, the distribution of predicted values, $P_Z$, forms a distributional lower bound on the distribution of true beliefs, $P$.

**Remark 1.** (Hendren (2013)) 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 true beliefs are a mean-preserving spread of the distribution of predicted values:

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

**Proof.** See Proposition 1 in Hendren (2013). \hfill \Box

Assumption (a) is a natural assumption to place on the elicitations, as it is difficult to imagine how someone could report more information than their true beliefs. Assumption (b) is potentially
more restrictive, as individuals may have biased beliefs. However, biased beliefs can still be incorpo-
ated by thinking of them as augmenting willingness to pay as opposed to the pooled price ratio.\textsuperscript{24} Even in the case of biased beliefs, the pooled price ratio, $T(p)$, derived from the unbiased beliefs present the key frictions imposed by private information, as they are relevant from the perspective of an insurance companies’ costs.

Under Assumptions (a) and (b), Remark 1 shows 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 these predicted values, aggregating across observable variables by subtracting out $\Pr \{U|X\}, P_Z - \Pr \{U|X\}$.\textsuperscript{25} 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, any point of risks on this figure would need to be willing to pay a large enough markup to cover the costs of the higher risks adversely selecting their contract. The theory provides a precise measure of this markup, $T(p)$, which is a function of the unobserved belief distribution, $P$. But, under assumptions (a) and (b) above, one can use the distribution of predicted values, $P_Z$, to form a lower bound on the average pooled price ratio, $E[T(P)]$.

**Proposition 1.** Under Assumptions (a) and (b) in Remark 1, one can form a non-parametric lower bound on the average pooled price ratio:

$$E[T(P)] \geq E[T_Z(P_Z)]$$

where

$$T_Z(p) = 1 + \frac{E[P_Z - p|P_Z \geq p]}{\Pr \{U\}}$$

**Proof.** See Appendix B.1. \qed

The numerator, $E[P_Z - p|P_Z \geq p]$, provides a lower bound on the average extent to which risks have higher probabilities than $p$; the denominator, $\Pr \{U\}$, normalizes this difference by the mean

\textsuperscript{24}In particular, one can augment the willingness to pay, $u'(c_u(p))u'(c_e(p))$, with $\beta(p)u'(c_u(p))u'(c_e(p))$, where $\beta(p)$ is the impact of belief bias on willingness to pay. For example, if individuals have a probability re-weighting function $\tilde{p}(p)$ as in Kahneman and Tversky (1979), one can write $\beta(p) = \tilde{p}(p)\frac{1-p}{1-p[1-p]}$. Then, the no trade condition remains identical to equation (2) with $\beta(p)u'(c_u(p))u'(c_e(p))$ on the LHS and the same pooled price ratio, $T(p)$, on the RHS that uses beliefs $p$ that satisfy Assumption (b).

\textsuperscript{25}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 $Z$. 

\textsuperscript{14}
probability of $U$ in the population to arrive at a measure of the markup individuals would have to be willing to pay to cover the cost of the higher risks. Appendix B.1 applies the results in Remark 1 combined with Jensen’s inequality to deliver the result in equation (4).

**Lower bounds on $E[T(P)]$** Table II presents the estimates of $E[T_z(P_z)] - 1$. 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 $E[T(P)] \geq 1.7682$. Unless individuals are willing to pay at least a markup of over 70% (i.e. $\frac{\mu'(\zeta_2)}{\sigma'(\zeta_2)} > 1.7$, an insurer would have difficulty profitably providing insurance due to adverse selection.

Of course, the amount of private information can depend on how much information, $X$, insurers use to price the insurance policies. Table II shows that adding health controls or dropping the job characteristic controls do not meaningfully change the results (71.98% and 80.33%, respectively). Figure III, Panel A, graphically illustrates these estimates of $E[T_z(P_z)] - 1$ plotted 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 controls. The additional job characteristics controls help better predict unemployment entry rates across industry and occupation groups; but the magnitude of $E[P_z - p|P_z \geq p]$ depends on the thickness of the upper tail of the distribution of predicted values, which does not appear to be significantly altered with these changes in controls, $X$. This is consistent with the upper tail being driven by 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 $\Pr \{U|X, Z\}$. Of

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26 As in Hendren (2013), 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 $m_z(p) = E[P_z - p|P_z \geq p]$ 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 (2013) 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 $X \in \zeta_j$. 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.

27 Appendix Table I explores robustness to various specifications, including linear versus probit error structures, alternative aggregation windows for constructing $E[m_z(P_z)]$, and alternative polynomials for $Z$. All estimates are quite similar to the baseline and yield lower bounds of $E[T_z(P_z)] - 1$ of around 70%.

28 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
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.\textsuperscript{29} 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.\textsuperscript{30}

**Estimates for Sub-samples** The remaining columns of Table II and panels of Figure II explore how the estimated markups vary across subsamples. This provides consistent estimates of $E[T_Z (P_Z)] − 1$ in excess of 50\% across industries (Figure II, Panel C), occupations (Panel D), age groups (Panel E), years (Appendix Figure I, Panel A) and census divisions (Appendix Figure I, Panel B).

One underwriting strategy that has been common in other insurance markets is to limit the insurance market to “good risks”.\textsuperscript{31} 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.

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\textsuperscript{29}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.

\textsuperscript{30}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 elicitations containing largely personal and time-varying knowledge about future job loss.

\textsuperscript{31}For example, health-related insurance markets generally exclude those with pre-existing conditions. Hendren (2013) 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.
Alternative outcomes and waiting periods  While the baseline results suggest insurers would face significant adverse selection if they tried to sell an insurance policy in the event that the applicant loses his or her job in the subsequent year after purchase, the insurer could potentially mitigate this by imposing waiting periods or making other modifications to when the insurance policy pays its benefits, $U$. Fortunately, the empirical strategy (i.e. Assumptions (a) and (b)) do not require that $Z$ be an elicitation that perfectly corresponds to an event, $U$. Hence, to explore whether such modifications would be profitable one can simply alter the construction of $U$ and use the same elicitation to construct lower bounds on $E[T(P)]$ for this alternative event.$^{32}$

Appendix Table I and Appendix Figure I (Panel C) report these estimated lower bounds for a range of alternative constructions of $U$. Requiring a 6-month waiting period so that the insurance policy pays only if the individual loses his or her job in the subsequent 6-12 months leads to a lower bound on $E[T(P)] – 1$ of 57.9% ($p < 0.001$). The markups remain high for other potential timelines, such as 0-24 and 6-24 month payout windows. Another strategy an insurer could take is to require an individual to also file for government UI.$^{33}$ However, this also does not reduce the lower bound on $E[T(P)] – 1$. In short, changing the definition of $U$ through waiting periods and attachment to government UI programs does not appear to remove or significantly reduce the barriers 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, $\inf T(p)$.

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 (2013) by making additional

$^{32}$I 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)).

$^{33}$Indeed, this is part of the strategy taken by the most recent attempt at providing unemployment insurance by Income Assure.
assumptions about the distribution of measurement error in the elicitations. 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 \( p \)).\(^{34}\) As shown in Hendren (2013), the key additional assumption required to move from lower bounds to point estimates is to place some structure on the distribution of elicitations given beliefs, \( f_{Z|P,X} \), to reduce its dimensionality. I assume elicitations are equal to beliefs plus a noise term, \( Z = P + \epsilon \), where \( \epsilon \) is drawn from a mixture of an ordered probit structure to capture the excess mass at focal point values. Appendix B.2 provides the precise details of the specification and the estimation of the minimum pooled price ratio.

**Results** Table III reports the results. I estimate a value of \( \inf T(p) - 1 \) of 3.36 in the baseline specification with demographic and job characteristic controls. 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%).\(^{35}\)

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.

Appendix Figure II places these estimates in the context of estimates from Hendren (2013), which uses the same empirical strategy to study private information in Long-Term Care insurance, Life insurance, and Disability insurance. The results suggest no statistically significant amounts of private information for those with observable characteristics that allow them to purchase insurance.

\(^{34}\)This is obtained by first taking the conditional expectation with respect to \( p \) and then using the assumption that \( \Pr \{ U|Z, X, P \} = P \).

\(^{35}\)Appendix Table II presents the raw point estimates for \( \alpha_i \) and \( \xi_i \). It suggests there is a small (e.g. 10%) subsample of the population that has a very high chance of losing their job. The presence of this upper tail drives these high estimated markups.
But, for those with pre-existing conditions that would cause them to be rejected by an insurance company, the estimated markups are 42% for Life, 66% for Disability, and 83% for Long-Term Care.

In this sense, the size of the barrier to trade imposed by private information about unemployment risk is an order of magnitude larger than what is found in these health-related insurance markets. This perhaps explains why no subsegments of the market appear to exist for UI. More generally, it is consistent with the hypothesis that the frictions imposed by private information form the boundary of the existence of insurance markets in these UI and health-related insurance markets. To make this argument more formally, one must also estimate the demand for insurance – an issue to which I now turn.

5 Demand for UI

How much of a markup would individuals be willing to pay for a private unemployment insurance contract? This section provides estimates of the markup individuals would be willing to pay for UI after learning their type $p$, $u'(c_u(p))$ $\frac{u''(c_u(p))}{u'(c_x(p))}$.

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. 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:

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

(5)

where $\frac{\Delta c}{c} = \frac{c_e(p) - c_u(p)}{c_e(p)}$ 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, $\sigma = \frac{c_e(p)u''(c_x(p))}{u'(c_x(p))}$. Following previous literature, it is common to approximate this percentage change using log consumption,

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

Hence, the willingness to pay for a type $p$ depends on the causal impact of unemployment on their log consumption. To begin, I focus on the average causal effect$^{36}$ scaled by the coefficient of relative risk aversion:

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

$^{36}$Later, I explore potential heterogeneity in $\frac{\Delta c}{c} (p)$ by analyzing the quantiles of the consumption response to unemployment.
where the superscript “$Ex^{\text{post}}$” refers to the fact that the measure of willingness to pay is measured after individuals learn their type, $p$.

In principle, one could attempt to estimate $W^{Ex^{\text{post}}}$ 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.

5.1 First Difference Impact of Unemployment

To remove selection bias, it is common to estimate the impact of unemployment on yearly consumption first differences (Gruber (1997); Chetty and Szeidl (2007)). Panel 1 of Table IV reports the coefficient from a regression of the change in log food expenditure relative to the previous year, $g_t = \log (c_t) - \log (c_{t-1})$, on an indicator for unemployment, $U_t$,

$$g_t = a + \Delta^{FD}U_t + \Gamma X_t + \epsilon_t$$

where $\Delta^{FD}$ is the impact of unemployment on the first difference in consumption, $g_t$, and $X_t$ are controls that include a cubic in the household head’s age and year dummies.

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 6.39% lower consumption (s.e. 0.556%), as shown in Column (1). Restricting to the sample who were employed in $t - 1$ yields a coefficient of 0.0753 (s.e. 0.857%), as shown in Column (2). Column (3) adds controls to the specification on Column (2) for the log change in household expenditure needs and the change in the number of household members (Column (3)), yielding a drop of 7.2% (s.e. 0.891%). Column (4) restricts to a sample of those above age 40 to more closely align with the HRS sample for whom the private information is identified; this yields a similar consumption drop of 6.09% (s.e. 1.5%).

The analysis in columns (1)-(4) make a couple of specification decisions whose robustness are explored in Columns (5) and (6). First, following Gruber (1997), outliers with more than a threefold change in food expenditure were dropped. Column (5) shows that re-introducing these observations increases the coefficient to -9.58% (s.e. 1.19%). Second, food expenditure sums 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 recall window could lead to an understating of the impact of unemployment on food consumption. To understand the potential impact of this, Column (6) expands the specification in Column (5) to exclude food stamp expenditure from the food expenditure measure altogether. This yields a larger expenditure drop of 16.4% (s.e. 1.58%), and provides arguably an upper bound on the size of the average expenditure drop.

The baseline analysis measures how food expenditure varies with whether or not the individual is employed at the time of measurement. However, the baseline definition of $U$ in Section (4) is job loss, which may or may not lead to unemployment at the point in time when the survey measures food expenditure. Column (7) measures the log expenditure impact of being laid off or fired from the job in the previous year, regardless of whether the individual is unemployed at the subsequent time of the survey. Food expenditure growth is 5.3% lower relative to the previous year if a job loss has occurred relative to the previous year. This is slightly lower than the 7.53% drop if one instead measures unemployment. Overall, this is consistent with the idea that consumption effects are attenuated when looking at job loss because the timing of the consumption measurement does not align with the timing of the event. Across the range of specifications, the results suggest a mean impact of unemployment on consumption growth of roughly 6-17%.

5.2 Bias from Ex-ante Response

If the impacts of unemployment on consumption growth, $\Delta^{FD}$, captured the causal effect of unemployment on consumption, then one could scale this estimate by the coefficient of relative risk aversion (e.g. 2 or 3) to arrive at the markup individuals are willing to pay for unemployment insurance, $W^{Ex-post}$. However, if individuals learn ex-ante about their potential future unemployment, lagged consumption may differ between subsequently employed and unemployed, even for those who were ex-ante identical. One can write the first difference estimate as:

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

where the bias term equals the difference in consumption in the year prior to the unemployment spell, $c_{pre}$, between those who subsequently become unemployed and those who do not.

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Footnotes:

37Columns (9)-(10) explore beyond the mean impacts by looking at quantile responses to provide potential insight into how much the willingness to pay, $\phi'(c,(p))$, may vary across different values of beliefs, $p$. Columns (9) and (10) report estimates from the quantile regression of changes in log food expenditure on unemployment. Column (9) reports the 10th percentile and Column (10) reports the 90th percentile. 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.
Figure IV explores the extent to which ex-ante consumption responses bias the estimates of the causal effect of unemployment on consumption. Figure IV plots the coefficients from a regression of food expenditure in year $t+j$, $g_{t+j}$, 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 $t-2$. Both figures document a drop in consumption not only upon the onset of unemployment, but also in the year prior to unemployment.\footnote{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 $t-2$.}

Panel 1 of 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) shows that the pattern in Figure IV, Panel A corresponds to a -3.13\% (s.e. 0.578\%) drop in expenditure in the year before unemployment occurs. Column (2) restricts the sample to those who are not unemployed in years $t-1$ and $t-2$, which attenuates the food expenditure drop slightly to -2.3\% (s.e. 0.954\%). This is to be expected, as unemployment status is autocorrelated at roughly 0.4 across years in the baseline sample. 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, delivering a similar coefficient of -2.32\% (s.e. 1.01\%) and suggesting the patterns are not driven by changes in household size or composition around the time of unemployment. Column (4) restricts the sample to those over age 40, yielding a coefficient of -2.04\% (s.e. 1.53\%) which is similar in magnitude but not statistically distinguishable from either the baseline estimate of 2.3\% or zero.\footnote{Appendix Figure VI replicates the baseline regression in Figure IV (Panel B) using more recent PSID data on total household expenditure on a sample that is surveyed every two years. The broad patterns are similar, although the consumption drop upon unemployment is slightly larger (e.g. 12\%) when using total consumption expenditure as opposed to food expenditure and not dropping outliers with less than a threefold change (Panel B). There is also an ex-ante response of 3.6\% ($p=0.055$) in $t-2$ relative to $t-4$ in total consumption expenditure.} Column (5) replaces the unemployment measure with a measure of job loss relative to the previous year of the survey. I restrict to a sample who have not experienced job loss in $t-1$ or $t-2$ and regress lagged food expenditure on the job loss indicator. This yields a coefficient of -1.82\% (s.e. 8.54\%) which is smaller but statistically indistinguishable from the baseline coefficient of -2.3\% in Column (2).\footnote{This attenuation is partially off-set by a consumption drop in years prior to $t-1$. To illustrate this, Online Appendix Figure IV replicates Figure IV, Panel B using job loss instead of the concurrent unemployment measure. The results suggest consumption falls slightly in the 1-3 years prior to the job loss.}

**Mechanisms: Forward looking behavior versus correlated shocks**

On the one hand, the ex-ante responses are consistent with forward looking behavior in response to a lower future income. To nest this into the theory in Section 2, let $v(c_{pre}(p))$ denote the utility from consumption at the
time of learning one’s type, \( p \). Under the assumption that the rate of return on savings equals the discount rate, the Euler equation implies:

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

(6)

The marginal utility of consumption today is equated to the expected marginal utility of consumption in the future. 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 \( p \). On the other hand, the ex-ante responses could also be consistent with individuals consuming hand-to-mouth \((c = y)\) if income drops prior to unemployment.\(^{42}\)

To distinguish between these mechanisms, Column (6) of Table V 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 2.29% (s.e. 0.947%) nearly identical to the baseline specification in Column (2). Column (7) adds controls for a third degree polynomial of changes in log income of the household head, yielding a coefficient of -2.31% (s.e. 0.963%).\(^{43}\) To understand why the results are not significantly affected by adding controls for income, Appendix Figure V replicates Figure IV (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 associated with any significant income change in any of the years prior to unemployment.\(^{44}\) In short, the consumption drop is consistent with an anticipatory response to future unemployment.

5.3 IV Correction

Because consumption response to future unemployment, the first difference estimate of the impact of unemployment on consumption does not deliver the causal effect of unemployment on consumption. This section provides a two-sample IV strategy to recover the causal effect from the first difference estimator by scaling it by the amount of information revealed over the time elapsed in the first difference (e.g. 1 year prior to unemployment).\(^{45}\)

\(^{41}\)Formally, I assume \( c_{\text{pre}} \) is an element of \( a \) in the model in Section 2 and that utility is additively separable in consumption over time.

\(^{42}\)For example, Davis and von Wachter (2011) find evidence that income drops in the year prior to large plant closings.

\(^{43}\)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.

\(^{44}\)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. The absence of an ex-ante drop in income differs from the findings of Davis and von Wachter (2011) for plant closings. To be sure, there are sub-samples in the PSID for which income does decline; in particular, if one includes those who are unemployed in \( t - 1 \) or \( t - 2 \), then income does decline prior to the unemployment measurement (as shown in Stephens (2001)).

\(^{45}\)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 \( \theta \), this
The Euler equation suggests that the size of the ex-ante consumption response should be related to the size of the causal effect of the unemployment event on consumption. Appendix C.1 shows that if the consumption drop is not varying with \( p \), \( \frac{d[\log(c_{e}(p)) - \log(c_{u}(p))]}{dp} = 0 \), then the impact of learning that unemployment is 1% more likely (i.e. \( p \) increases by 1pp) is equal to 1% of the causal effect of unemployment on consumption. In this case, one can recover the average causal effect of unemployment on log consumption by scaling by the amount of information revealed in the year long period before the unemployment period.

**Proposition 2.** Suppose the Euler equation 6 holds and the consumption drop is not varying with \( p \), \( \frac{d[\log(c_{e}(p)) - \log(c_{u}(p))]}{dp} = 0 \). Let “\( \approx \)” denote an equality up to log-linear consumption approximations and second-order Taylor approximations for \( u \) and \( v \). Then, the average causal effect of unemployment on log consumption is given by

\[
E[\log(c_{e}(p)) - \log(c_{u}(p))] \approx \frac{\Delta_{FD}^{IV}}{1 - \kappa (E[P|U = 1] - E[P|U = 0])} \equiv \Delta_{IV}
\]

where \( \frac{\text{var}(P)}{\text{var}(U)} = E[P|U = 1] - E[P|U = 0] \) is the fraction of variance in \( U \) that is realized in beliefs \( P \) at time \( t-1 \) and \( \kappa = E\left[\frac{1}{1 + p(u'(c_{u}(p)) - u'(c_{e}(p)))}\right] \approx 1 \).

If the consumption drop varies with \( p \), then \( \Delta_{IV} \) is greater than (less than) \( E[\log(c_{e}(p)) - \log(c_{u}(p))] \if higher values of \( p \) correspond to larger (smaller) consumption drops.\(^{46}\)

**Proof.** See Appendix C.1. \( \square \)

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, and the first difference estimate remains valid. 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.

As shown in Appendix C.1, the \( \kappa \) correction factor in the denominator of \( \Delta_{IV} \) corrects for the fact that the ex-ante consumption response is valued using the ex-ante marginal utility, whereas 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.\(^{46}\)

In particular, one can show:

\[
E[\log(c_{e}(p)) - \log(c_{u}(p))] = \frac{\Delta_{FD}^{IV} + \frac{d[\log(c_{e}(p)) - \log(c_{u}(p))]}{dp} (E[P|U = 1] - E[P])}{1 - \kappa (E[P|U = 1] - E[P|U = 0]) - E[P] \sigma \frac{d[\log(c_{e}(p)) - \log(c_{u}(p))]}{dp}}
\]

where \( \sigma \) is the coefficient of relative risk aversion.
the insurance markup is defined relative to the marginal utility in the ex-post state of employment. Because $p$ is small, this correction is minor (i.e. $\kappa \approx 1$); if individuals are willing to pay a 25% markup and $E[p] = 4\%$, then this correction factor is 1.01. Therefore, going forward I assume $\kappa \approx 1$.

5.4 2-Sample Implementation

I do not observe consumption concurrently with beliefs in the HRS samples. As a result, I estimate the denominator in equation (7) using the subjective probability elicitation and unemployment data from the HRS. I regress the subjective probability elicitations on an indicator for subsequent unemployment. This provides 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 $P$.47

Returning to Table IV, Panel 2 presents the estimates of the first stage in the denominator of equation (7). The estimates suggest $E[P|U = 1] - E[P|U = 0] \approx 0.197$ (s.e. 0.012), which suggests roughly 80% of the uncertainty in unemployment is not known 1 year in advance. Of course, the HRS sample is a more recent and older sample than the PSID sample that yields the food expenditure impacts. However, Appendix Table IV explores the robustness of this estimate across subgroups (age, gender, year) and shows that this 80% figure remains quite stable across sub-samples.48

Panel 3 scales the estimates in Panel 1 by this first stage to arrive at an estimate of the average causal impact of unemployment on consumption. For the baseline sample employed in $t - 1$, unemployment causes a 9.4% consumption drop (Column (2)). Across the other specifications, the causal impact ranges between 7-26%. For a coefficient of relative risk aversion of $\sigma = 2$, the 9.4% drop implies an willingness to pay for unemployment insurance of 18.7%. This is largely similar across specifications, but significantly increases to 41% when not including food stamps in food expenditure as shown in Column (6). Columns (8) and (9) show that this estimate rises to 51.1% for quantiles with the 90th percentile of the consumption drop and is actually negative (-7.9%) for the 10th percentile consumption drop. This suggests that there may be significant heterogeneity in the populations’ willingness to pay for UI.

However, all of these estimates remain well below the estimated 300%+ markups shown in Table III. This suggests that private information provides a rationale for the absence of a private market for UI.49 If insurers were to attempt to sell a UI policy, it would be too heavily adversely selected

$^{47}$Because $P$ and $U$ are bounded variables, the classical measurement error assumption is unlikely to be literally true, but it is a useful benchmark.

$^{48}$For example, restricting the analysis in the HRS to pre-1997 data from males age 55 and under yields an estimate of 79.1% (s.e. 6.27%).

$^{49}$Formally, this suggests individuals are not willing to pay to overcome the hurdles imposed by private information.
to deliver a positive profit.

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 conditional on what individuals know – some types (e.g. the “good risks”) would be worse off, whereas other types (e.g. the “bad risks”) would be better off.\footnote{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.}

However, the endowment is not the only constrained-efficient allocation. From an ex-ante perspective behind the veil of ignorance, individuals would prefer a level of benefits that maximizes the average level of utility across types. To reach this allocation, a government can force the good risks to pay for insurance and accept utility levels below their endowment with no insurance.

This section solves for the optimal level of UI benefits individuals would prefer prior to learning their type, $\theta$. The formulas suggest UI has value not only as insurance against the realization of unemployment conditional on one’s knowledge about their own risk, but also as insurance against learning one might lose their job. I provide methods to estimate this additional value in Section (7) below.

6.1 A Modified Baily-Chetty Condition

To begin, return to the model in Section 2 and consider the optimal level of benefits, $b$, financed with taxes $\tau$. This maximizes a utilitarian welfare function,

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

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, he shows the consumption drop would be roughly 25% (Table I, 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.
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 \( a(\theta) \)).\(^{51}\) In contrast to private markets, the government does not face a participation constraint: it can force everyone to pay premiums, \( \tau \), so that the budget constraint involves the entire population, as opposed to an adversely selected subset.

**Proposition 3.** (Modified Baily-Chetty Condition) The level of \( b \) and \( \tau \) that maximizes utilitarian welfare solves the modified Baily-Chetty condition:

\[ W_{Social} = FE \]  \hspace{1cm} (8)

where

\[
W_{Social} = \frac{E \left[ \frac{p}{E[p]} u'(c_u(p)) \right]}{E \left[ \frac{(1-p)}{E[1-p]} v'(c_e(p)) \right]} - 1 \]  \hspace{1cm} (9)

and

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

So that \( W_{Social} \) 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. If \( p \) is the only margin of adjustment, then \( FE = \frac{e_{p,b}}{1 - E[p(\theta)]} \), where \( e_{p,b} \) is the elasticity of \( p \) with respect to benefits, \( b \).\(^{52}\)

**Proof.** See Appendix C.4.

The intuition for equation (8) is straightforward. The fiscal externality term, \( FE \), is the causal effect of the behavioral response to additional UI on the government budget. This captures the cost to the government of providing UI beyond simply its mechanical cost of paying benefits. By the envelop theorem these behavioral responses are not valued by the individual beneficiaries, but they do impose a cost on the government. Often, models assume that the only response is on the

---

\(^{51}\)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.

\(^{52}\)The derivative, \( \frac{d}{db} \), is the causal effect of a simultaneous budget-neutral increase in benefits and taxes. In this sense, it is a policy elasticity defined in Hendren (2015).
duration or likelihood of unemployment, in which case $FE$ has a simple representation; but more generally it should include the aggregate causal effect on the government budget (Hendren (2015)).

The term, $W^{Social}$, is a measure of the ex-ante consumption smoothing benefits of UI. 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 $pu'$. The cost to the government of providing an additional dollar of benefits is proportional to the average probability of unemployment in the population, $E[p]$. If $p = E[p]$ so that there is no ex-ante realization of information, then $W^{Social} = \frac{u'(c_u)}{v'(c_e)} - 1 = W^{Ex-post}$. Hence, the formula in equation (8) would reduce to the canonical Baily-Chetty condition. But more generally if there is some ex-ante knowledge about whether unemployment will occur, individuals value UI not only because it insures against unemployment conditional on $p$, but it also partially insures against the realization of $p$.

In this sense, the social value of UI includes the role of providing insurance against the risk of future unemployment, $p(\theta)$. To see this, 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:

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

(10)

The ex-ante value of insurance measures how much ex-ante marginal utilities increase for those with higher ex-ante beliefs, $p$. For simplicity, I assume $\frac{d\log(v'(c_{pre}(p)))}{dp}$ is constant for all $p$. Under the same assumptions required for Proposition 2 to hold, Appendix C.3 shows that the social value of UI is a weighted average of the ex-ante and ex-post willingness to pay:

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

(11)

where $\frac{\text{var}(P)}{\text{var}(U)} = E[P|U=1] - E[P|U=0]$ is the fraction of information individuals know about $U$. If information about $U$ is fully revealed in beliefs, $P$, then $\text{var}(P) = \text{var}(U)$ so that $W^{Ex-ante}$ characterizes the social willingness to pay for UI. If individuals have no knowledge of future unemployment, then $\text{var}(P) = 0$ and $W^{Ex-post}$ characterizes the social value of UI.\footnote{More formally, the derivation shows that}

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

which, under the approximation $(1 + x)(1 + y) \approx 1 + x + y$ yields equation (11).

\footnote{Appendix C.3 also derives equation (11) for the case where the consumption drop varies with $p$. If higher values of $p$ correspond to larger (smaller) consumption drops, then the true social willingness to pay is larger (smaller) than is implied by equation (11) which uses the average willingness to pay measures, $W^{Ex-ante}$ and $W^{Ex-post}$.}
Interestingly, under state-independence \((u = v)\), the second term in equation (11), \(\left(1 - \frac{\text{var}(P)}{\text{var}(U)}\right)W_{E \text{Ex-post}}\), is equal to \(\sigma \Delta^{FD} \) – the first difference estimate of unemployment on consumption, as in Gruber (1997). In this sense, the first term in equation (11) characterizes the portion of the social value of UI that has been missed in previous literature: the value of insurance against learning one might become unemployed.

7 Ex-Ante Willingness to Pay

This section provides two approaches to estimating the willingness to pay for insurance against learning one might lose their job, \(W_{E \text{Ex-ante}}\). The first approach uses ex-ante consumption responses; the second approach uses ex-ante spousal labor supply responses.

7.1 Consumption

Expanding equation (10) using the consumption response to beliefs yields:

\[
W_{E \text{Ex-ante}} \approx \sigma_v \frac{-d \log (c_{\text{pre}} (p))}{dp}
\]  

(12)

where \(\sigma_v = \frac{-\psi_v'}{v'}\) is the coefficient of relative risk aversion (evaluated at \(c_{\text{pre}} (0)\)). If learning one may lose their job corresponds to lower consumption, \(c_{\text{pre}}\), individuals value transfers to states of the world with higher beliefs, \(p\), in proportion for those with higher beliefs, \(p\), \(W_{E \text{Ex-ante}}\) measures the percentage change in ex-ante marginal utilities from a percentile increase in the likelihood of unemployment.

The ex-ante welfare impact of UI depends on the relationship to beliefs, \(p\), and consumption, \(c_{\text{pre}}\). To identify this relationship, Table V applies the 2-sample IV strategy in Section 5 to the consumption response in the year before the unemployment measurement.

Consumption drops 2.5% in the year before unemployment. To arrive at an estimate of \(\frac{d \log (c_{\text{pre}})}{dp}\), this 2.5% consumption drop needs to be scaled by the amount by which information is revealed between 2 and 1 year prior to the unemployment measurement. 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:

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

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 $E[\text{P}_{t-2,t}|U_t = 1] - E[\text{P}_{t-2,t}|U_t = 0]$, 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 $E[\text{P}_{t-2,t}|U_t = 1] - E[\text{P}_{t-2,t}|U_t = 0]$ if the error is uncorrelated with $U$ conditional on $\text{P}_{t-2,t}$, 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 $E[\text{P}_{t-2,t}|U_t = 1] - E[\text{P}_{t-2,t}|U_t = 0] = 0.0937$, which implies a value of $\Delta$First Stage = 0.1031 (s.e. 0.0121), as shown in the first row of Panel 2.\textsuperscript{55} These estimates are obtained using the full HRS sample; Appendix Table IV also reports estimates of the first stage on sub-samples of the data that more closely align with the PSID sample, which yields similar estimates.\textsuperscript{56}

Panel 2 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 $\frac{\text{dlog}(\text{cre})}{\text{dp}} = 0.22$ (s.e. 0.09). This suggests learning one is 10% more likely to lose their job would cause a 2.2% drop in consumption. Scaling this estimate by a coefficient of relative risk aversion of $\sigma = 2$, it implies $W^{ex-ante} = 0.45$ (s.e. 0.19). This suggests individuals would be willing to pay a 45% markup for insurance against learning they might lose their job. The remaining columns illustrate the robustness of the estimates to other specifications. These results generally fall around 35-50%, indicating significant ex-ante value of unemployment insurance.

### 7.2 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. This section presents evidence that the risk of future job loss increases spousal labor entry into the labor market. These responses are then used to provide an

\textsuperscript{55}Online Appendix Figure III also reports the coefficients for future years of unemployment and obtains estimates of $E[Z_{t-1,t}|U_t = 1] - E[Z_{t-1,t}|U_t = 0]$ ranging from 0.1 to 0.05 at $j = 8$, which suggests most of the information 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 IV.

\textsuperscript{56}For example, the first stage rises slightly to 0.123 (s.e. 0.013) when using only pre-1997 data. It falls to 0.0812 (s.e. 0.0192) when using only those below age 55. On the sample of males age 55 and under using only pre-1997 data, I obtain a first stage of 0.1635 (s.e. 0.06), which is again not statistically distinct from the full sample estimates. As a result, I rely on the full sample for the baseline specifications presented here.
additional measure of the ex-ante value of unemployment insurance.

**Data** I exploit data in the HRS that contains information both subjective probability elicitation and spousal labor supply information. I utilize the sample of households married in both the current and previous wave of the survey. To avoid bias from correlated shocks to labor earning opportunities (e.g. spouses working at the same firm or same industry), the primary analysis will analyze labor market entry by the spouse. This is defined 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 over the two years between the previous and current wave of the survey.

**Results** Figure V plots the coefficients on bins of the subjective probability elicitation controlling for census region, year, age, age squared, gender, marital status, the log wage, and an indicator for the future realization of unemployment. Figure V illustrates that those with higher elicitation 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 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.\(^{57}\)

Table VI linearly parameterizes the relationship in Figure V. 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 includes shifts from part time to full time work in the definition of labor market entry, and finds a similar slope of 0.0278 (s.e. 0.00975).

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. The current results suggest a portion of these responses occur even before the onset of unemployment.
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, a countervailing force could arise from correlated labor demand shocks (e.g. from spouses working in the same industry). To explore these patterns, 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. The coefficient of 0.0170 (s.e. 0.0116) is positive, although not statistically significant. This suggests spouses are perhaps slightly more likely to exit, consistent with households facing correlated unemployment shocks. 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 C.2 shows that

$$W_{Ex-ante} \approx \frac{d\phi}{dp} \frac{1}{e^{semi}}$$

(13)
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 implicitly reveals the ex-ante valuation of UI.

Panel 2 of Table VI translates the estimates into their implications for \( W_{Ex-ante} \) using equation (13). 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 \( Z \).

The results suggest that individuals would be willing to pay a 60% markup, \( W_{Ex-ante} \approx 60\% \), for insurance against the event of learning they are going to lose their job in the baseline specification. The other specifications generate similar measures, consistent with 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. Individuals derive significant value from insurance against the risk of learning they might lose their job.

**Ex-Ante versus Ex-Post Willingness to Pay**  
\( W_{Ex-ante} \) identifies the willingness to pay that individuals have to provide payments proportional to their likelihood of experiencing unemployment, \( p \). In this sense, it provides partial insurance against any shock that causes \( p \) to increase. In contrast, \( W_{Ex-post} \) identifies the willingness to pay that individuals have to insure against the realization of unemployment conditional on what they know today, \( p \).

Across specifications, the ex-ante willingness to pay is generally higher than the ex-post willingness to pay. A priori, this relationship is ambiguous. On the one hand, learning about future unemployment allows one to take actions to mitigate its impact, lowering the ex-ante value of insurance. On the other hand, the type of shocks that cause the increase in unemployment risk (e.g. shocks to industry, occupation, or location labor demand) may generate adverse labor market consequences going forward. The high value of \( W_{Ex-ante} \) is consistent with individuals having significant value for insurance against these latter effects.

\[^{58}\text{I construct } \text{var}(Z|X) \text{ as the square of the RMSE of a regression of } Z \text{ on the control variables. I construct } \text{var}(P|X) \text{ as } \text{var}(P|X) \approx \text{cov}(Z,L|X), \text{ where the approximation would hold exactly if the measurement error in } Z \text{ were classical. To construct } \text{cov}(Z,L|X), \text{ I first residualize } L \text{ and } Z \text{ on } X \text{ and then calculate the covariance of the residuals, then adjust for the degrees of freedom introduced in the initial residualization.}\]

33
### 7.3 Social Value of UI

Table VII presents the results for $W^{Social}$ by taking the variance-weighted average the ex-ante and ex-post value of insurance, following equation (11). I draw upon the baseline specifications for the impact of unemployment on consumption in Tables IV-VI and present robustness to a range of assumptions over the coefficient of relative risk aversion, $\sigma$, and the semi-elasticity of spousal labor supply, $\varepsilon^{semi}$.

For a coefficient of relative risk aversion of 2, the results suggest an ex-ante willingness to pay a markup of 44.54% against the realization of $p$ but only a 18.75% markup against the realization of $U$ given $p$. This suggests that the total social value of insurance is 23.8%. 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 62%; combining this with the ex-post willingness to pay of 18.9% yields a total willingness to pay of 27.3%.

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%.

While the precise willingness to pay for UI is sensitive to assumptions about $\sigma$ and $\varepsilon^{semi}$, the results consistently suggest that the ex-ante value of insurance comprises a large fraction of the overall social value of UI. The third row of Table VII reports the fraction of $W^{Social}$ that is not captured by previous estimates that measure the value of UI using $\sigma \Delta^{FD}$ (e.g. Gruber (1997)). For the consumption specifications, the results suggest that the ex-ante value of insurance comprises 36.8% of the total social value of UI, $W^{Social}$, $\frac{W^{Social} - \sigma \Delta^{FD}}{W^{Social}} = 36.8\%$. This percentage increases to 44.7% when one uses the spousal labor supply response to measure $W^{Ex-ante}$ for $\varepsilon^{semi} = 0.5$; it decreases to 35.1 for $\varepsilon^{semi} = 0.75$ and increases to 61.8% for $\varepsilon^{semi} = 0.25$, as higher labor supply elasticities imply a lower value of ex-ante insurance (all else equal). Overall, the estimates suggest that a large share – roughly 35-40% – of the social value of UI is captured in the ex-ante value

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59 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).

60 Note that 90% of information is revealed by $t - 2$, so that one must extrapolate to obtain the ex-ante value of UI prior to 2 years before the unemployment measurement. This calculation assumes that the value of $W^{Ex-ante}$ that applies to the information revealed between $t - 2$ and $t - 1$ also applies to the information revealed prior to $t - 2$. With additional data on the belief and consumption evolution around the onset of unemployment, one could generate more precise estimates of $W^{Ex-ante}$ prior to the 2 years before the unemployment measurement.
of insurance. Individuals value government UI not only because it insures against the realization of unemployment conditional on what they know today; but also because it provides imperfect insurance against learning today that they might lose their job.

8 Conclusion

This paper argues that private information prevents the existence of a robust private market for unemployment or job-loss insurance. If insurers were to attempt to sell such policies, they would be too heavily adversely selected to deliver positive profit. Combined with the results in Hendren (2013) shown in Online Appendix Figure II, they suggest the frictions imposed by private information determine the existence of insurance markets.

This micro-foundation for the absence of a private market changes the way one should think about optimal social intervention in insurance markets. If individuals learn about unemployment before it actually occurs, they can derive value from unemployment insurance because it insures not only against the realization of unemployment conditional on their currently known risk but also as insurance against learning one might lose their job. Traditional welfare analyses miss this value of insurance, and the analyses above suggest that more than 35% of the value of UI is realized a year before measuring the unemployment incident. This suggests an importance for greater consideration of the time path of information revelation when thinking about the private and social demand for insurance.

References


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A No Trade Condition

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

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

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

which will be positive if and only if

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

The LHS of equation (14) 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.\(^61\) The RHS of equation (14), \( \frac{d\tau}{db} \), is the cost per dollar of benefits of the insurance 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 (14)). 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

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

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 additional insurance on its cost. If more insurance increases the probability of unemployment, \( dE[p(\theta)] > 0 \), then it reduces premiums collected, \( \tau \), and increases benefits paid, \( b \).\(^62\)

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

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

\[
\frac{d\tau}{db} \geq \frac{E[p(\theta)]_{\theta \in \Theta (\frac{d\tau}{db})}}{E[1 - p(\theta)]_{\theta \in \Theta (\frac{d\tau}{db})}}
\]

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

To this point, the model allows for an arbitrary dimensionality of unobserved heterogeneity, \( \theta \). 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 dimensionality reduction on the unobserved heterogeneity.

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

Assumption A1 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.

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

\(^62\)To incorporate observable characteristics, one should think of the expectations as drawing from the distribution of \( \theta \) conditional on a particular observable characteristic, \( X \).

\(^63\)See Appendix A.3 for a micro-foundation of this assumption.
without a private unemployment insurance market, \( b = \tau = 0 \).\(^{64}\) And, let \( c_u (p) \) and \( c_e (p) \) denote the consumption of types \( p (\theta) \) in the unemployed and employed states of the world. Under Assumption A1, equation (15) can be re-written as:

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

where \( T (p) \) is given by

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

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

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

A.1 Multi-Dimensional Heterogeneity

This section solves for the no-trade condition when there does not exist a one-to-one mapping between \( \theta \) and \( p (\theta) \). In this case, 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 \( \frac{u'(c_u (\theta))}{v'(c_e (\theta))} \) 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

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

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 all types above \( \tilde{p} \left( \frac{d\tau}{db} \right) \). Without loss of generality, one can assume that \( \tilde{p} \) is strictly increasing in \( \frac{d\tau}{db} \) so that \( \tilde{p}^{-1} \) exists.\(^{65}\)

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

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

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

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

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

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

\[
\frac{E[p(\theta) \mid \theta \in \Theta(\frac{d\xi}{d\theta})]}{E[1 - p(\theta) \mid \theta \in \Theta(\frac{d\xi}{d\theta})]} = \frac{E[p(\theta) \mid p(\theta) \geq \tilde{p}(\frac{d\xi}{d\theta})]}{1 - E[p(\theta) \mid p(\theta) \geq \tilde{p}(\frac{d\xi}{d\theta})]}
\]

so that we wish to show that

\[
\frac{E[p(\theta) \mid p(\theta) \geq \tilde{p}(\frac{d\xi}{d\theta})]}{1 - E[p(\theta) \mid p(\theta) \geq \tilde{p}(\frac{d\xi}{d\theta})]} \geq \frac{d\tau}{db}
\]

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

\[
\frac{E[p(\theta) \mid p(\theta) \geq \tilde{p}]}{1 - E[p(\theta) \mid p(\theta) \geq \tilde{p}]} \geq \tilde{p}^{-1}(p) \quad \forall p \in A
\]

which is equivalent to

\[
\frac{E[p(\theta) \mid p(\theta) \geq \tilde{p}]}{1 - E[p(\theta) \mid p(\theta) \geq \tilde{p}]} \geq \frac{p - u'(c_e(f(p)))}{1 - p v'(c_u(f(p)))} \quad \forall p \in A
\]

which proves the desired result.

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

### A.2 Robustness to Menus

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

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

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

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

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

\[
\pi(\Delta, \nu; \theta) = \hat{q}(\Delta; \theta)(c_e - C_e(v - \Psi(\Delta; \theta))) + (1 - \hat{q}(\Delta; \theta)) (c_u - C_u(v - \Delta - \Psi(\Delta; \theta)))
\]

Note that the profit function takes into account how the agents’ choice of \( p \) varies with \( \Delta \).

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

I prove the sufficiency of the no-trade condition for ruling out trade by mapping it into the setting of Hendren (2013). To do so, define \( \hat{\pi}(\nu, \Delta; \theta) \) 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
\[
\pi (\nu, \Delta; \theta) \leq \pi (\nu, \Delta; \theta)
\]

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 \( \Pi \),
\[
\Pi (\nu (\theta), \Delta (\theta)) = \int \pi (\nu (\theta), \Delta (\theta); \theta) \, d\mu (\theta)
\]
So, for small variations in \( \nu \) and \( \Delta \), we have that
\[
\Pi (\nu (\theta), \Delta (\theta)) \leq \Pi (\nu (\theta), \Delta (\theta))
\]
because insurance causes an increase in \( p \). Now, Hendren (2013) shows that the no trade condition implies that \( \Pi \leq 0 \) 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 Assumption and Sufficient Conditions for Concavity

The presence of moral hazard in this multi-dimensional screening problem induces the potential for non-convexities in the constraint set. Such non convexities could potentially limit the ability of local variational analysis to characterize the set of implementable allocations. To be specific, let \( \pi (\Delta, \mu; \theta) \) denote the profit obtained from type \( \theta \) if she is provided with total utility \( \mu \) and difference in utilities \( \Delta \),
\[
\pi (\Delta, \mu; \theta) = (1 - \hat{\rho} (\Delta; \theta)) (c^e - C_u (\mu - \Psi (1 - \hat{\rho} (\Delta; \theta)))) + \hat{\rho} (\Delta; \theta) (c^e - C_u (\mu - \Delta - \Psi (1 - \hat{\rho} (\Delta; \theta))))
\]
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 this extends to the case when \( p \) is a choice and can respond to \( \theta \).

**Claim.** If \( \Psi'' (q; \theta) > 0 \) for all \( \theta \) and \( \frac{\nu (c^e)}{\nu (c^e)} \leq 2 \) then \( \pi \) is globally concave in \( (\mu, \Delta) \).

For simplicity, we consider a fixed \( \theta \) and drop reference to it. Profits are given by
\[
\pi (\Delta, \mu) = \hat{\rho} (\Delta) (c^e - C_u (\mu - \Psi (\hat{\rho} (\Delta)))) + (1 - \hat{\rho} (\Delta)) (c^e - C_u (\mu - \Delta - \Psi (\hat{\rho} (\Delta))))
\]
The goal is to show the Hessian of \( \pi \) is negative semi-definite. I proceed in three steps. First, I derive conditions which guarantee \( \frac{\partial^2 \pi}{\partial \Delta^2} < 0 \). Second, I show that, in general, we have \( \frac{\partial^2 \pi}{\partial \mu^2} < 0 \). Finally, I show the conditions provided to guarantees \( \frac{\partial^2 \pi}{\partial \Delta \partial \mu} < 0 \) also imply the determinant of the Hessian is positive, so that both eigenvalues of the Hessian must be negative and thus the matrix is negative semi-definite.

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

Taking the first derivative with respect to \( \Delta \), we have
\[
\frac{\partial \pi}{\partial \Delta} = \frac{\partial \hat{\rho}}{\partial \Delta} (c^e - c^u + C_u (\mu - \Delta - \Psi (\hat{\rho} (\Delta))))
\]
\[
- (1 - \hat{\rho} (\Delta)) C'_u (\mu - \Delta - \Psi (\hat{\rho} (\Delta))) - \hat{\rho} (\Delta) C'_e (\mu - \Psi (\hat{\rho} (\Delta)))
\]

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

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
\[(1 + \hat{q}(\Delta)) C' (\mu - \Delta - \Psi(\hat{\Delta})) \geq \hat{q}(\Delta) C' (\mu - \Delta)\]
which is necessarily true whenever
\[
\frac{u'(c_e^\nu)}{v'(c_h^\nu)} \leq 2
\]
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 $\frac{\partial^2 \hat{q}}{\partial \Delta^2} = -\frac{\Psi''(\hat{\Delta})}{(\Psi'(\hat{\Delta}))^2}$. Therefore, if we assume that $\Psi'' > 0$, the entire last term will necessarily be negative. In sum, it is sufficient to assume $\frac{u'(c_e^\nu)}{v'(c_h^\nu)} \leq 2$ and $\Psi'' > 0$ to guarantee that $\frac{\partial^2 \pi}{\partial \mu^2} < 0$.

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

Fortunately, profits are easily seen to be concave in $\mu$. We have
\[
\frac{\partial \pi}{\partial \mu} = -(1 - \hat{q}(\Delta)) C'(\mu - \Delta - \Psi(\hat{\Delta})) - \hat{q}(\Delta) C'(\mu - \Psi(\hat{\Delta}))
\]
so that
\[
\frac{\partial^2 \pi}{\partial \mu^2} = -(1 - \hat{q}(\Delta)) C''(\mu - \Delta - \Psi(\hat{\Delta})) - \hat{q}(\Delta) C''(\mu - \Psi(\hat{\Delta}))
\]
which is negative because $C'' > 0$.

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

Finally, we need to ensure that the determinant of the Hessian is positive. To do so, first note that
\[
\frac{\partial^2 \pi}{\partial \mu \partial \Delta} = (1 - \hat{q}(\Delta)) C''(\mu - \Delta - \Psi(\hat{\Delta})) (1 + \Delta \hat{q}'(\Delta)) + \hat{q}(\Delta) C''(\mu - \Psi(\hat{\Delta})) \Delta \hat{q}'(\Delta)
\]
Also, we note that under the assumptions $\Psi'' > 0$ and $\frac{u'(c_e^\nu)}{v'(c_h^\nu)} \leq 2$, we have the inequality
\[
\frac{\partial^2 \pi}{\partial \Delta^2} < - \left[ (1 - \hat{q}(\Delta)) (1 + \Delta)^2 C^\mu_\nu (\mu - \Delta - \Psi(\hat{\Delta})) + \hat{q}(\Delta) (\Delta \hat{q}'(\Delta))^2 C''(\mu - \Psi(\hat{\Delta})) \right]
\]

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 $\frac{\partial^2 \pi}{\partial \Delta \partial \mu}$ and subtract $\left( \frac{\partial^2 \pi}{\partial \Delta \partial \mu} \right)^2$. Fortunately, many of the terms cancel out, leaving the inequality
\[
\frac{\partial^2 \pi}{\partial \Delta^2} \frac{\partial^2 \pi}{\partial \mu^2} - \left( \frac{\partial^2 \pi}{\partial \Delta \partial \mu} \right)^2 \geq (1 - \hat{q}(\Delta)) \hat{q}(\Delta) (1 + \Delta \hat{q}'(\Delta))^2 C''(\mu - \Delta - \Psi(\hat{\Delta})) C''(\mu - \Psi(\hat{\Delta})) + \hat{q}(\Delta) (\Delta \hat{q}'(\Delta))^2 C''(\mu - \Psi(\hat{\Delta})) C''(\mu - \Psi(\hat{\Delta}))
\]
\[+ \hat{q}(\Delta) (1 - \hat{q}(\Delta)) (\Delta \hat{q}'(\Delta))^2 C''(\mu - \Psi(\hat{\Delta})) C''(\mu - \Delta - \Psi(\hat{\Delta})) - 2 (1 - \hat{q}(\Delta)) \hat{q}(\Delta) (1 + \Delta \hat{q}'(\Delta)) \Delta \hat{q}'(\Delta) C''(\mu - \Delta - \Psi(\hat{\Delta})) C''(\mu - \Psi(\hat{\Delta}))\]
which reduces to the inequality
\[
\frac{\partial^2 \pi}{\partial \Delta^2} \frac{\partial^2 \pi}{\partial \mu^2} - \left( \frac{\partial^2 \pi}{\partial \Delta \partial \mu} \right)^2 \geq \hat{q}(\Delta) (1 - \hat{q}(\Delta)) C''(\mu - \Delta - \Psi(\hat{\Delta})) C''(\mu - \Psi(\hat{\Delta})) K(\mu, \Delta)
\]
where
\[
K(\mu, \Delta) = (1 + \Delta \hat{q}'(\Delta))^2 + (\Delta \hat{q}'(\Delta))^2 - 2 \Delta \hat{q}'(\Delta) - 2(\Delta \hat{q}'(\Delta))^2
\]

So, since \( C'' > 0 \), we have that the determinant must be positive. In particular, we have
\[
\frac{\partial^2 \pi}{\partial \Delta^2 \partial \mu^2} - \left( \frac{\partial^2 \pi}{\partial \Delta \partial \mu} \right)^2 \geq \hat{q}(\Delta)(1 - \hat{q}(\Delta))C''(\mu - \Delta - \Psi(\hat{q}(\Delta)))C''(\mu - \Psi(\hat{q}(\Delta)))
\]

### A.3.4 Summary

As long as \( \Psi'' > 0 \) and \( \frac{u'(c_e)}{v'(c_e)} \leq 2 \), the profit function is globally concave. Empirically, I find 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 \( \Delta \) on the employment probability is declining in the size of \( \Delta \). Put differently, it is an assumption that providing utility incentives to work has diminishing returns.

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

### A.4 Motivating the Average Pooled Price Ratio when Insurers don’t know \( P \)

To see the theoretical relevance of \( E[T(P)] \), suppose an insurer seeks to start an insurance market by randomly drawing an individual from the population and, perhaps through some market research, learns exactly how much this individual is willing to pay. The insurer offers a contract that collects $1 in the event of being employed and pays an amount in the unemployed state that makes the individual perfectly indifferent to the policy. If \( p \) is the probability this individual will become unemployed, then all risks \( P \geq p \) will choose to purchase the policy as well. The profit per dollar of revenue will be
\[
r(P) = \frac{u'(c_u(p))}{v'(c_u(p))} - T(p)
\]

So, if the original individual was selected at random from the population, the expected profit per dollar would be positive if and only if
\[
E\left[ \frac{u'(c_u(p))}{v'(c_u(p))} \right] \geq E[T(P)]
\]

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

### B Details of Empirical Approach

#### B.1 Proof of Proposition 1

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

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

**Proof:** note that
\[
m(P) = E[P - p | P \geq p]
\]

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

So, we wish to show that
\[
E\left[ \frac{m(P)}{P} \right] < E\left[ \frac{m(P)}{P} \right]
\]

**Note that:**
\[
E\left[ \frac{m(P)}{P} \right] = E\left[ \frac{1}{-P^2} \int (\bar{p} - P) f(\bar{p}) \, d\bar{p} \right] = E\left[ \frac{E[\bar{p} | \bar{p} \geq P]}{P} \right] - 1 = E_\bar{p}E_{\bar{p}} \left[ \frac{\bar{p} \times \bar{p} \geq P}{P} \geq 1 \right] - 1
\]
And:

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

So, we wish to test whether

\[ E_{\mathcal{P}}E_{\mathcal{P}}\left[ \frac{\bar{p}}{E[P]} \big| \bar{p} \geq P \right] < \gamma \]

or

\[ E_{\mathcal{P}}E_{\mathcal{P}}\left[ \frac{\bar{p}}{E[P]} - \frac{1}{E[P]} \big| \bar{p} \geq P \right] > \gamma \]

or

\[ E_{\mathcal{P}}E_{\mathcal{P} \geq P}\left[ \frac{\bar{p}}{E[P]} \left( \frac{1}{P} - \frac{1}{E[P]} \right) \big| \bar{p} \geq P \right] > \gamma \]

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

\[ E_{\mathcal{P}}E_{\mathcal{P} \geq P}\left[ \frac{\bar{p}}{E[P]} \left( \frac{1}{P} - \frac{1}{E[P]} \right) \big| \bar{p} \geq P \right] \geq E_{\mathcal{P}}E_{\mathcal{P} \geq P}\left[ P \left( \frac{1}{P} - \frac{1}{E[P]} \right) \big| \bar{p} \geq P \right] \]

\[ \geq E_{\mathcal{P}} \left[ \frac{1}{E[P]} \big| \bar{p} \geq P \right] \]

\[ \geq 0 \]

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

**Proof of Proposition.**

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

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

\[ \geq E_{\mathcal{P}} \left[ \frac{1 + m(P)}{P} \right] \]

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

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,

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

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

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.

**B.2 Specification for Point Estimation**

I follow Hendren (2013) 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); Manski and Molinari (2010)). 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 κ and 1 − κ, they report 50; and if it would have been above 1 − κ, they report 1. Hence, I estimate four elicitation error parameters: (σ, λ, κ, α (X)) that capture the patterns of noise and bias in the relationship between true beliefs, P, and the elicitations reported on the surveys, Z.66

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

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

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

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

\[
\tilde{F} (p|q) = w \{ p \leq q - a \} + (1 - w) \sum \xi_i 1 \{ p \leq \alpha_i \}
\]

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 (2013), estimation of the minimum \( T (p) \) across the full support of the type distribution is not feasible because of an extremal quantile estimation problem. To keep the estimates “in-sample”, I report values for the mean value of \( q = \Pr \{U\} = 0.031 \); but estimates at other values of \( q \) are similarly large.

C Welfare Metrics

C.1 Proof of Proposition 2

Note under state independence, the Euler equation implies

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

66Specifically, the p.d.f./p.m.f. of Z given \( P \) is given by

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

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

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

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

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

\[ u''(c_{\text{pre}}(p)) \frac{dc_{\text{pre}}}{dp} = u'(c_{\text{u}}(p)) - u'(c_{r}(p)) + pu''(c_{\text{u}}(p)) \frac{dc_{\text{u}}}{dp} + (1 - p) u''(c_{\text{r}}(p)) \frac{dc_{\text{r}}}{dp} \]

Dividing,

\[ \frac{u'(c_{\text{pre}}(p)) u''(c_{\text{pre}}(p))}{u'(c_{\text{pre}}(p))} \frac{dc_{\text{pre}}}{dp} = u'(c_{r}) \frac{u'(c_{\text{u}}(p)) - u'(c_{r}(p))}{u'(c_{\text{r}}(p))} + pu'(c_{\text{u}}(p)) \frac{dc_{\text{u}}}{u'(c_{\text{r}}(p))} + (1 - p) u'(c_{r}) \frac{u''(c_{\text{r}}(p))}{u'(c_{\text{r}}(p))} \frac{dc_{\text{r}}}{dp} \]

or

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

So, dividing by \( u'(c_{r}) \) yields:

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

And, using the Euler equation, \( pu'(c_{\text{u}}(p)) + (1 - p) u'(c_{r}(p)) = u'(c_{\text{pre}}(p)) \),

\[ \frac{pu'(c_{\text{u}}(p)) + (1 - p) u'(c_{r}(p))}{u'(c_{r})} \frac{-\text{dlog}(c_{\text{pre}})}{dp} = \frac{u'(c_{\text{u}}(p)) - u'(c_{r}(p))}{u'(c_{r})} + \frac{pu'(c_{\text{u}}(p))}{u'(c_{r})} \frac{-\text{dlog}(c_{\text{u}}(p))}{dp} + (1 - p) \frac{-\text{dlog}(c_{\text{r}}(p))}{dp} \]

so that

\[ \frac{-\text{dlog}(c_{\text{pre}})}{dp} = \frac{\frac{u'(c_{\text{u}}(p))}{u'(c_{r})} - 1}{1 + p \left( \frac{u'(c_{\text{u}}(p))}{u'(c_{r})} - 1 \right)} \frac{-\text{dlog}(c_{\text{r}}(p))}{dp} + \frac{pu'(c_{\text{u}}(p))}{u'(c_{r})} \frac{-\text{dlog}(c_{\text{u}}(p))}{dp} + (1 - p) \frac{-\text{dlog}(c_{\text{r}}(p))}{dp} \]

or

\[ \frac{-\text{dlog}(c_{\text{pre}})}{dp} = \frac{\frac{u'(c_{\text{u}}(p))}{u'(c_{r})} - 1}{1 + p \left( \frac{u'(c_{\text{u}}(p))}{u'(c_{r})} - 1 \right)} \frac{-\text{dlog}(c_{\text{r}}(p))}{dp} + \frac{pu'(c_{\text{u}}(p))}{u'(c_{r})} \frac{-\text{dlog}(c_{\text{u}}(p))}{dp} + (1 - p) \frac{-\text{dlog}(c_{\text{r}}(p))}{dp} \]

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

\[ \frac{-\text{dlog}(c_{\text{pre}})}{dp} = \frac{1}{\sigma} \left( \frac{u'(c_{\text{u}}(p))}{u'(c_{r})} - 1 \right) E \left[ \frac{1}{1 + p \left( \frac{u'(c_{\text{u}}(p))}{u'(c_{r})} - 1 \right)} \frac{-\text{dlog}(c_{\text{r}}(p))}{dp} + E \left[ \frac{pu'(c_{\text{u}}(p))}{u'(c_{r})} \frac{-\text{dlog}(c_{\text{u}}(p))}{dp} + (1 - p) \frac{-\text{dlog}(c_{\text{r}}(p))}{dp} \right] \right] \]

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

Note also that

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

which implies

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

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:

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

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

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

Note that \( c = c_{u} \) for those with \( U_{t} = 1 \) and \( c = c_{r} \) for those with \( U = 0 \). The following three equations help expand \( \Delta^{FD} \):

\[ E \left[ \text{log}(c_{-1}) \right] | U = 1] - E \left[ \text{log}(c_{-1}) \right] | U = 0] = \frac{d \text{log}(c_{\text{pre}})}{dp} \frac{\text{var}(P)}{\text{var}(U)} \]
and
\[ E[\log(c) | U = 1] - E[\log(c) | U = 0] = E[\log(c_u) | U = 1] - E[\log(c_u) | U = 1] \]
\[ = E[\log(c_u) - \log(c_e)] + \frac{d[\log(c_u) - \log(c_e)]}{dp} (E[P | U = 1] - E[P]) \]

and
\[ E[\log(c) | U = 1] - E[\log(c) | U = 0] = E[\log(c_u) | U = 1] - E[\log(c_u) | U = 0] \]
\[ = \frac{d\log(c_e) \var(U)}{dp} \]

So, substituting these into \( \Delta^{FD} \) yields:
\[ \Delta^{FD} = E[\log(c) - \log(c_e)] - \frac{\var(P)}{\var(U)} \left[ \kappa (E[\log(c) - \log(c_u)] + E[P] \frac{u'(c_u)}{u'(c_e)} \frac{d[\log(c) - \log(c_u)]}{dp} \right] \]
\[ = \frac{d[\log(c) - \log(c_u)]}{dp} (E[P | U = 1] - E[P]) \]

Let \( \frac{d\Delta}{dp} = \frac{d([\log(c_u) - \log(c_e)])}{dp} \) denote how the consumption drop varies with \( p \). Solving for \( E[\log(c) - \log(c_e)] \) yields
\[ E[\log(c) - \log(c_e)] = \frac{\Delta^{FD} + \frac{d\Delta}{dp}}{1 - \frac{\var(P)}{\var(U)} \kappa - \bar{\rho} \frac{d\Delta}{dp}} \]

where \( \kappa = \) which yields the desired result. Note that if the consumption drop does not vary with \( p \), then this reduces to
\[ E[\log(c) - \log(c_e)] = \frac{\Delta^{FD}}{1 - \frac{\var(P)}{\var(U)} \kappa} \equiv \Delta^{IV} \]

More generally, if the size of the consumption drop is increasing with \( p \), then \( E[\log(c) - \log(c_e)] > \Delta^{IV} \).

### C.2 Ex-ante labor supply derivation

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

Spousal labor force participation generates income, \( y \), but has an additively separable effort cost, \( \eta(\theta) \). I assume a spousal labor supply decision, \( l \in \{0, 1\} \), is a binary decision and is contained in the set of other actions, \( a \). Formally, let
\[ \Psi(1 - p, a, \theta) = \bar{\Psi}(1 - p, \bar{a}, \theta) + 1 \{l = 1\} \eta(\theta) \]

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

Let \( k(y, l, p) \) denote the utility value to a type \( p \) of choosing \( l \) to obtain income \( y \) when they face an unemployment probability of \( p \). The labor supply decision is
\[ k(y, 1, p) - k(0, 0, p) \geq \eta(\theta) \]
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
\[ \frac{d\Phi}{dp} = f(\bar{\eta}) \frac{\partial \bar{\eta}}{dp} = f(\bar{\eta}) \left[ \frac{\partial k(y, 1, p)}{dp} - \frac{\partial k(0, 0, p)}{dp} \right] \]
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
\[ \frac{d\Phi}{dp} \approx f(\bar{\eta}) \frac{\partial^2 k}{dp^2} y \]

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 \( p \) yields
\[ E_p \left[ \frac{d\Phi}{dp} \right] \approx E_p \left[ f(\bar{\eta}) \frac{d}{dp} v'(c_{\text{pre}}(p)) y \right] \]
To compare this response to a wage elasticity, consider the response to a $1 increase in wages

\[
\frac{d\Phi}{dy} = f(\bar{y}) \frac{\partial k}{\partial y}
\]

so,

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

Now, let \( \varepsilon_{semi} \) denote the semi-elasticity of spousal labor force participation. This yields

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

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

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

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

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

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

This section shows that

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

under the assumption that \( u = v \) and that \( \frac{d\log(c_u)}{dp} = \frac{d\log(c_v)}{dp} = \frac{d\log(c_{post})}{dp} \).

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

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

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

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

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 \( \bar{c}_v = E[c_v] \). Using a Taylor expansion for \( u' \) yields

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

\[
\approx -\sigma \text{var} \left( \frac{p}{\bar{p}} \frac{(c_u - \bar{c}_u)}{c_u} \right)
\]

\[
\approx -\sigma \text{var} \left( \frac{p}{\bar{p}} \frac{\log(c_u)}{c_u} \right)
\]

\[
\approx -\sigma \left( \frac{\text{var}(p) \frac{d\log(c_u)}{dp}}{\bar{p}} \right)
\]

Similarly,

\[
\text{cov} \left( \frac{p}{1 - \bar{p}} \frac{u'(c_v)}{E[u'(c_v)]} \right) \approx -\sigma \frac{\text{var}(p) \frac{d\log(c_u)}{dp}}{1 - \bar{p}}
\]
So that
\[ \text{cov} \left( \frac{p}{\hat{p}} \frac{u'}{(c_u)} \right) + \text{cov} \left( \frac{p}{1 - \hat{p}} \frac{u'}{(c_u)} \right) \approx -\sigma \frac{\text{var}(p)}{\hat{p}(1 - \hat{p})} \frac{d\log(c_p)}{dp} + \frac{1}{\hat{p}} \frac{d[\log(c_e) - \log(c_u)]}{dp} \]

and note
\[ \frac{\text{var}(p)}{\hat{p}(1 - \hat{p})} = E[P|U = 1] - E[P|U = 0] \]

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

Now, Section C.1 shows that the Euler equation implies
\[ \frac{-d\log(c_{\text{pre}})}{dp} = E[\log(c_e(p)) - \log(c_u(p))] \kappa + \frac{-d\log(c_p)}{dp} + E \left[ \frac{p \frac{u'(c_u(p))}{u'(c_u(p))}}{\hat{p} \frac{u'(c_u(p))}{u'(c_u(p))} + 1 - \hat{p}} \left[ \frac{-d\log(c_p)}{dp} \right] \right] \]

so that
\[ \sigma \left[ \frac{-d\log(c_{\text{pre}})}{dp} - E[\log(c_e) - \log(c_u)] \right] = \frac{\text{cov} \left( \frac{p}{\hat{p}} \frac{u'}{(c_u)} \right) + \text{cov} \left( \frac{p}{1 - \hat{p}} \frac{u'}{(c_u)} \right)}{\hat{p} \frac{u'(c_u(p))}{u'(c_u(p))} + 1 - \hat{p}} \left[ \frac{-d\log(c_p)}{dp} \right] \]

or
\[ \sigma \left[ \frac{-d\log(c_{\text{pre}})}{dp} - E[\log(c_e) - \log(c_u)] \right] = \frac{1}{\hat{p}} \left( 1 - \frac{\text{var}(p)}{\hat{p}(1 - \hat{p})} \right) \left[ \frac{-d\log(c_p)}{dp} \right] \]

or
\[ \frac{W_{\text{Ex-ante}} - W_{\text{Ex-post}}}{dP} \left( E[P|U = 1] - E[P|U = 0] \right) + \frac{1}{\hat{p}} \left( 1 - \sigma \frac{\text{var}(p)}{\hat{p}(1 - \hat{p})} \right) \left[ \frac{-d\log(c_p)}{dp} \right] \]

So, if \( \frac{d[\log(c_e) - \log(c_u)]}{dp} = 0 \), then
\[ \text{cov} \left( \frac{p}{\hat{p}} \frac{u'}{(c_u)} \right) + \text{cov} \left( \frac{p}{1 - \hat{p}} \frac{u'}{(c_u)} \right) \approx \left( W_{\text{Ex-ante}} - W_{\text{Ex-post}} \right) \left( E[P|U = 1] - E[P|U = 0] \right) \]

Additionally, note that
\[ \frac{E[u'(c_u)]}{E[u'(c_u)]} \approx 1 + \frac{\sigma_{E} - \sigma_{E}}{\sigma_{E}} \approx 1 + \sigma \left( E[\log(c_e) - \log(c_u)] \right) \]

Combining, we have
\[ W_{\text{Social}} + \approx (1 + \sigma \left( E[\log(c_e) - \log(c_u)] \right)) \left( 1 + \sigma \left( \frac{-d\log(c_{\text{pre}})}{dp} - E[\log(c_e) - \log(c_u)] \right) \right) \frac{\text{var}(p)}{\text{var}(U)} \]

So that if \( \frac{d[\log(c_e) - \log(c_u)]}{dp} = 0 \),
\[ 1 + W_{\text{Social}} \approx \left( 1 + W_{\text{Ex-post}} \right) \left( 1 + \frac{\text{var}(p)}{\text{var}(U)} \right) \left( W_{\text{Ex-ante}} - W_{\text{Ex-post}} \right) \]

Now, approximating \( (1 + x)(1 + y) \approx 1 + x + y \) yields
\[ W_{\text{Social}} \approx \left( 1 - \frac{\text{var}(p)}{\text{var}(U)} \right) W_{\text{Ex-post}} + \frac{\text{var}(p)}{\text{var}(U)} W_{\text{Ex-ante}} \]
More generally, if \( \frac{d[\log(c_a) - \log(c_b)]}{dp} \neq 0 \), then

\[
W_{Social} \approx \left(1 - \frac{\text{var}(P)}{\text{var}(U)}\right) W_{Ex-post} + \frac{\text{var}(P)}{\text{var}(U)} W_{Ex-ante} + \frac{1}{p} \left(1 - \sigma \frac{\text{var}(P)}{1-p} E\left[\frac{p u'(c_a(p))}{p u'(c_a(p)) + 1 - p}\right] \right) \frac{d[\log(c_e) - \log(c_u)]}{dp}
\]

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

C.4 Modified Baily-Chetty Condition

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

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

where

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

is the increased premium required to cover the cost of additional benefits, which includes the impact of the behavioral response, \( \frac{d}{db} \left[\frac{E[p(\theta)]}{1 - E[p(\theta)]} + T(a(\theta))\right] \). Note this includes the response from additional unemployment entry (e.g. \( \frac{dE[p(\theta)]}{db} \)) 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 (2015) – 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:

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

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

So, the optimality condition becomes:

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

where

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

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).
<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>Selected Observables (subset of $X$)</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>Unemployment Outcome ($U$)</td>
<td>0.031</td>
<td>0.173</td>
<td>0.032</td>
</tr>
<tr>
<td>Subjective Probability Elicitation ($Z$)</td>
<td>15.7</td>
<td>24.8</td>
<td>15.7</td>
</tr>
<tr>
<td>Spousal Labor Supply</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>Sample Size</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 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>
<thead>
<tr>
<th>Specification:</th>
<th>Baseline (1)</th>
<th>Demo (2)</th>
<th>Health (3)</th>
<th>Sub-Samples</th>
<th>Age &lt;= 55</th>
<th>Age &gt; 55</th>
<th>Median Wage</th>
<th>Median Wage</th>
<th>Tenure &gt; 5 yrs</th>
<th>Tenure &lt;= 5 yrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>E[T(P)-1]</td>
<td>0.7682</td>
<td>0.8033</td>
<td>0.7198</td>
<td></td>
<td>0.6983</td>
<td>0.8150</td>
<td>0.6513</td>
<td>0.9515</td>
<td>1.0996</td>
<td>0.4759</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.053)</td>
<td>(0.051)</td>
<td>(0.052)</td>
<td></td>
<td>(0.081)</td>
<td>(0.066)</td>
<td>(0.058)</td>
<td>(0.094)</td>
<td>(0.093)</td>
<td>(0.057)</td>
</tr>
<tr>
<td>E[m(P)]</td>
<td>0.0236</td>
<td>0.0247</td>
<td>0.0228</td>
<td></td>
<td>0.0208</td>
<td>0.0256</td>
<td>0.0244</td>
<td>0.0228</td>
<td>0.0192</td>
<td>0.0270</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td></td>
<td>(0.003)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>p-value</td>
<td>0.0000</td>
<td>0.0000</td>
<td>0.0000</td>
<td></td>
<td>0.0000</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>0.0307</td>
<td>0.0307</td>
<td>0.0317</td>
<td></td>
<td>0.0297</td>
<td>0.0314</td>
<td>0.0375</td>
<td>0.0239</td>
<td>0.0175</td>
<td>0.0568</td>
</tr>
</tbody>
</table>

Controls
Demographics: X X X X X X X X
Job Characteristics: 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(P)]/Pr{U=1}. The value of E[m(P)] 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(P)] and E[m(P)] are constructed using 500 bootstrap resamples at the household level.
<table>
<thead>
<tr>
<th>Specification</th>
<th>Baseline</th>
<th>Demo</th>
<th>Health</th>
<th>Sub-Samples</th>
<th>Age &lt;= 55</th>
<th>Age &gt; 55</th>
<th>Below Median Wage</th>
<th>Above Median Wage</th>
<th>Tenure &gt; 5 yrs</th>
<th>Tenure &lt;= 5 yrs</th>
</tr>
</thead>
<tbody>
<tr>
<td>s.e.</td>
<td>(0.203)</td>
<td>(0.655)</td>
<td>(0.268)</td>
<td></td>
<td>(0.306)</td>
<td>(0.279)</td>
<td>(0.417)</td>
<td>(0.268)</td>
<td>(0.392)</td>
<td>(0.336)</td>
</tr>
</tbody>
</table>

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

Num of Obs. | 26,640 | 26,640 | 22,831 | 11,134 | 15,506 | 13,320 | 13,320 | 17,850 | 8,790 |
Num of HHs  | 3,467  | 3,467  | 3,180  | 2,255  | 3,231  | 2,916  | 2,259  | 2,952  | 2,437 |

Notes: This table presents estimates of the 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 Over 40 Sample</th>
<th>With Outliers</th>
<th>With Outliers; no food stamps</th>
<th>Job Loss</th>
<th>p10</th>
<th>p90</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
<td>(8)</td>
</tr>
<tr>
<td><strong>Panel 1: Reduced Form Impact on log(c&lt;sub&gt;t&lt;/sub&gt;-1)-log(c&lt;sub&gt;t&lt;/sub&gt;)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemp</td>
<td>-0.0639***</td>
<td>-0.0753***</td>
<td>-0.0720***</td>
<td>-0.0609***</td>
<td>-0.0958***</td>
<td>-0.161***</td>
<td>-0.0509***</td>
<td>0.0318**</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.00556)</td>
<td>(0.00857)</td>
<td>(0.00891)</td>
<td>(0.0150)</td>
<td>(0.0119)</td>
<td>(0.0158)</td>
<td>(0.00772)</td>
<td>(0.0246)</td>
</tr>
<tr>
<td><strong>Specification Details</strong></td>
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<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>X</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>X</td>
</tr>
<tr>
<td>Individual Fixed Effects</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>0.048</td>
<td>0.048</td>
<td>0.050</td>
<td>0.030</td>
<td>0.056</td>
<td>0.057</td>
<td>0.048</td>
<td>0.048</td>
</tr>
<tr>
<td>Num of Obs.</td>
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<td>80263</td>
<td>66679</td>
<td>29772</td>
<td>8174</td>
<td>81810</td>
<td>80604</td>
<td>80263</td>
</tr>
<tr>
<td>Num of HHs</td>
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<td>11252</td>
<td>10424</td>
<td>5515</td>
<td>11398</td>
<td>11186</td>
<td>11450</td>
<td></td>
</tr>
</tbody>
</table>

| **Panel 2: First Stage Impact on P** |             |                  |                                   |              |                                |          |     |     |
| Δ<sup>test</sup> Stage | 0.803*** | 0.803*** | 0.803*** | 0.803*** | 0.803*** | 0.803*** | 0.803*** | 0.803*** | 0.803*** |
| s.e.           | (0.012)   | (0.012)         | (0.012)                          | (0.012)     | (0.012)                       | (0.012)  | (0.012) | (0.012) | (0.012) |

| **Panel 3: Implied Causal Effect on Consumption** |             |                  |                                   |              |                                |          |     |     |
| IV Impact of U on log(c<sub>t</sub>) | -0.08*** | -0.094*** | -0.09*** | -0.076*** | -0.119*** | -0.204*** | -0.063*** | -0.256*** | 0.04*** |
| s.e.           | (0.007)   | (0.011)         | (0.011)                          | (0.019)     | (0.015)                       | (0.020)  | (0.010) | (0.031) | (0.016) |
| Markup WTP for UI (σ = 2) | 15.9% | 18.7% | 17.9% | 15.2% | 23.9% | 40.8% | 12.7% | 51.1% | -7.9% |

**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 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 (5) restricts the sample to those 40 and over for the specification in Column (3). Column (6) replaces the unemployment indicator with an indicator for job loss (both as the dependent variable and in restricting the sample to not having a job loss in the previous year). Job loss is defined as an indicator for being laid off or fired. Column (7) presents the results from a quantile regression at the 10th quantile for the specification in Column (2). Column (8) presents the results from a quantile regression at the 90th 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. All standard errors in Columns (1)-(6) are clustered at the household level. The quantile regressions in Columns (7)-(8) 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 1-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 (1-E[P|U=1] - E[P|U=0]). 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>Over 40 Sample</th>
<th>Job Loss</th>
<th>Household Income Controls</th>
<th>Household Head Income Controls</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
<td>(7)</td>
</tr>
<tr>
<td>Panel 1: Impact of Unemployment on log(c_{t-2})-log(c_{t-1})</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Unemp</td>
<td>-0.0313***</td>
<td>-0.0230**</td>
<td>-0.0232**</td>
<td>-0.0204</td>
<td>-0.0182**</td>
<td>-0.0229**</td>
<td>-0.0231**</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.00578)</td>
<td>(0.00954)</td>
<td>(0.0101)</td>
<td>(0.0153)</td>
<td>(0.00854)</td>
<td>(0.00947)</td>
<td>(0.00963)</td>
</tr>
<tr>
<td>Specification Details</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sample Employed in t-2 and t-1</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
<td>X</td>
</tr>
<tr>
<td>Controls for change in log needs (t-2 vs t-1)</td>
<td>X</td>
<td>X</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individual Fixed Effects</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Change in log HH inc (t-2 vs t-1) (3rd order poly)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>X</td>
</tr>
<tr>
<td>Change in log HH head inc (t-2 vs t-1) (3rd order poly)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean Dep Var</td>
<td>0.049</td>
<td>0.053</td>
<td>0.054</td>
<td>0.036</td>
<td>0.052</td>
<td>0.053</td>
<td>0.053</td>
</tr>
<tr>
<td>Num of Obs.</td>
<td>79312</td>
<td>69224</td>
<td>57590</td>
<td>26433</td>
<td>68791</td>
<td>69136</td>
<td>67818</td>
</tr>
<tr>
<td>Num of HHs</td>
<td>11006</td>
<td>10008</td>
<td>8819</td>
<td>4750</td>
<td>10171</td>
<td>9999</td>
<td>9893</td>
</tr>
<tr>
<td>Panel 2: Split-Sample IV Welfare Calculation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Δ_tot Stage</td>
<td>0.103</td>
<td>0.103</td>
<td>0.103</td>
<td>0.103</td>
<td>0.103</td>
<td>0.103</td>
<td>0.103</td>
</tr>
<tr>
<td>bootstrap s.e.</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>
<tr>
<td>d[log(c_{pt}-p))/dp (2-sample 2SLS)</td>
<td>0.3***</td>
<td>0.22***</td>
<td>0.23**</td>
<td>0.20</td>
<td>0.18**</td>
<td>0.22***</td>
<td>0.22***</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.06)</td>
<td>(0.09)</td>
<td>(0.10)</td>
<td>(0.15)</td>
<td>(0.08)</td>
<td>(0.09)</td>
<td>(0.09)</td>
</tr>
<tr>
<td>W^{ex-ante} (σ = 2)</td>
<td>0.61***</td>
<td>0.45***</td>
<td>0.45**</td>
<td>0.39</td>
<td>0.35**</td>
<td>0.44***</td>
<td>0.45***</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.11)</td>
<td>(0.19)</td>
<td>(0.20)</td>
<td>(0.30)</td>
<td>(0.17)</td>
<td>(0.18)</td>
<td>(0.19)</td>
</tr>
</tbody>
</table>

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 (5) restricts the sample to those 40 and over for the specification in Column (3). Column (5) replaces the unemployment indicator with an indicator for job loss (both as the dependent variable and in restricting the sample to not having a job loss in the previous 2 years). Job loss is defined as an indicator for being laid off or fired. Column (6) 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 (7) 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 elicitations. 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 repetitions). 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 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 VI
Spousal Labor Supply Response to Potential Job Loss and Implied (Ex-Ante) Willingness to Pay for UI

<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></td>
<td>Panel 1: Estimation of $dL/dZ$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></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></td>
<td>Panel 2: Welfare Calculation</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total Var / Signal Var ($\text{var}(Z</td>
<td>X)/\text{var}(P</td>
<td>X)$)</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>$W_{\text{ex-ante}}$ ($\epsilon_{\text{semi}} = 0.5$)</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>11049</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 ($\text{var}(P)$). 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 $0.0273 \times 11 / 0.5 = 0.60$. 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></td>
<td></td>
</tr>
<tr>
<td>WTP using $\sigma \Delta F$ (Gruber 1997)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fraction of $W_{social}$ that is Ex-ante</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Ex-ante and Ex-post Components</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>Insurance against $p$, $W_{ex-ante}$</td>
<td></td>
<td></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></td>
<td></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>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
<th>(7)</th>
<th>(8)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Spousal Labor Supply Semi-Elasticity, $\varepsilon_{semi}$</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>0.50</td>
<td>0.25</td>
<td>0.75</td>
<td>0.50</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 $p$).
<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</td>
<td>P_2)-1])</td>
<td>0.7687</td>
<td>0.6802</td>
<td>0.7716</td>
<td>0.7058</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_4</td>
<td>P_2])</td>
<td>0.0239</td>
<td>0.0209</td>
<td>0.0237</td>
<td>0.0217</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>
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<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 \(E[m_4|P_2]\). While Column (1) constructs \(m_4(P_2)\) using the predicted values within age-by-gender groups, Column (3) aggregates the predicted values across the entire sample. Column (4) uses a finer partition, aggregating within age-by-gender-by-industry groups. Column (5) aggregates within age-by-gender-by-occupation groups. Columns (6)-(7) consider alternative specifications for the subjective probability elicitations. Column (6) uses only a linear specification in \(Z\) combined with focal point indicators at \(Z=0, Z=50,\) and \(Z=100\), as opposed to the baseline specification that also includes a polynomial in \(Z\). Column (7) adds a third and fourth order polynomial in \(Z\) to the baseline specification. Columns (8)-(10) consider alternative outcome definitions for \(U\). Column (8) defines unemployment, \(U\), as an indicator for involuntary job loss at any point in between survey waves (24 months). Column (9) defines unemployment as an indicator for job loss in between survey waves excluding the first six months after the survey (i.e. 6-24 months). Finally, Column (10) defines unemployment as an indicator for job loss in the 6-12 months after the survey wave.
### APPENDIX TABLE II

**Estimation of \( F(p|X) \)**

<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>1st mass</td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Location</td>
<td>0.001</td>
<td>0.012</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.001)</td>
<td>(0.002)</td>
</tr>
<tr>
<td>Weight</td>
<td>0.446</td>
<td>0.713</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.024)</td>
<td>(0.071)</td>
</tr>
<tr>
<td>( T(p) )</td>
<td>43.839</td>
<td>6.301</td>
</tr>
<tr>
<td>s.e.</td>
<td>6.1E+06</td>
<td>1.7E+00</td>
</tr>
<tr>
<td>2nd mass</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Location</td>
<td>0.031</td>
<td>0.031</td>
</tr>
<tr>
<td>s.e.</td>
<td>N/A</td>
<td>N/A</td>
</tr>
<tr>
<td>Weight</td>
<td>0.471</td>
<td>0.202</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.024)</td>
<td>(0.071)</td>
</tr>
<tr>
<td>( T(p) )</td>
<td>4.360</td>
<td>8.492</td>
</tr>
<tr>
<td>s.e.</td>
<td>0.203</td>
<td>4.194</td>
</tr>
<tr>
<td>3rd Mass</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Location</td>
<td>0.641</td>
<td>0.639</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.004)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Weight</td>
<td>0.082</td>
<td>0.086</td>
</tr>
<tr>
<td>s.e.</td>
<td>(0.002)</td>
<td>(0.002)</td>
</tr>
</tbody>
</table>

**Controls**
- Demographics
- Job Characteristics
- Health Characteristics

**Notes:** This table presents estimates of the distribution of private information about unemployment risk, \( P \). Column (1) reports the baseline specification. Columns (2) uses only demographic controls; Column (3) uses demographic, job characteristics, and health characteristics. Columns (4)-(9) report results for the baseline specification on various subsamples including below and above age 55 (Columns 4 and 5), above and below-median wage earners (Columns 6 and 7) and above and below 5 years of job tenure. The \( F(p) \) estimates report the location and mass given to each point mass, evaluated at the mean \( q = P(U=1) = 0.031 \). 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>39.749</td>
<td>10.24</td>
</tr>
<tr>
<td>Male</td>
<td>0.810</td>
<td>0.39</td>
</tr>
<tr>
<td>Unemployment</td>
<td>0.057</td>
<td>0.23</td>
</tr>
<tr>
<td>Year</td>
<td>1985</td>
<td>7.66</td>
</tr>
<tr>
<td>Log Consumption</td>
<td>8.204</td>
<td>0.65</td>
</tr>
<tr>
<td>Log Expenditure Needs</td>
<td>8.125</td>
<td>0.32</td>
</tr>
<tr>
<td>Consumption growth (log(c,2)-log(c,1))</td>
<td>0.049</td>
<td>0.358</td>
</tr>
</tbody>
</table>

Sample Size

| Number of Observations                        | 79,312|
| Number of Households                          | 11,006|

Notes: This table presents the summary statistics for the PSID sample used to estimate the impact of future unemployment on consumption growth in the year prior to unemployment. I use data from the PSID for years 1971-1997. Sample includes all household heads with non-missing variables.
### APPENDIX TABLE IV
Information Realization Between t-2 and t-1 ("First Stage")

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

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

A. Control Variations

B. Controls (with Ind. FE)

C. By Industry

D. By Occupation

E. By Age

F. Low Risk Sub-samples

Notes: These figures present estimates of the lower bounds on the average pooled price ratio, $E\left[ T_Z(P_Z) \right]$, using a range of sub-samples and controls. Panel A reports estimates of $E\left[ T_Z(P_Z) \right]$ 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 Pseudo-$R^2$ 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 $E\left[ T_Z(P_Z) \right]$ and restrictions to lower-risk subsamples. The horizontal axis in Panels C-F report the mean unemployment probability, $Pr\{U\}$, for each sub-sample.
FIGURE IV: Impact of Unemployment on Consumption Growth

A. Full Sample

<table>
<thead>
<tr>
<th>Coefficient on Unemployment Indicator</th>
<th>5%/95% CI</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
</tr>
<tr>
<td>-0.08</td>
<td></td>
</tr>
<tr>
<td>-0.06</td>
<td></td>
</tr>
<tr>
<td>-0.04</td>
<td></td>
</tr>
<tr>
<td>-0.02</td>
<td></td>
</tr>
<tr>
<td>0</td>
<td></td>
</tr>
<tr>
<td>0.02</td>
<td></td>
</tr>
</tbody>
</table>

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). 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 $t - 2$. 
FIGURE V: Relationship between Potential Job Loss and Spousal Labor Supply

Notes: The figure presents 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 elicitation, $\mathbf{Z}$, 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: This figure presents additional estimates of the lower bound on the average pooled price ratio, $E\left[T_z(P_z)\right]$. Panel A reports separate estimates for each wave of the survey and Panel B reports estimates by census division. Panel C reports a set of estimates that use alternative definitions of $U$. This includes an indicator for involuntarily losing one’s job for three time windows: in between surveys (0-24 months), in the 6-12 months after the survey, and 6-24 months after the survey. The 6-12 and 6-24 month specifications simulate lower bounds on $E\left[T_z(P_z)\right]$ in a hypothetical underwriting scenario whereby insurers would impose 6 month waiting periods. I also include specifications that interact these indicators with indicators that the individual had positive government UI claims, which effectively restricts to the subset of unemployment spells where the individual takes up government UI benefits.
Notes: Hendren (2013) argues private information prevents people with pre-existing conditions from purchasing insurance in LTC, Life, and Disability insurance markets. This figure compares the estimates of $\inf T(p) - 1$ for the baseline specification in the unemployment context to the estimates in Hendren (2013) for the sample of individuals who are unable to purchase insurance due to a pre-existing condition (blue circles) and those whose observables would allow them to purchase insurance in each market (red hollow circles). Figure reports the confidence interval and the 5% / 95% confidence interval for each estimate in each sample. For the sub-samples in LTC, Life, and Disability for which the market exists, one cannot reject the null hypothesis of no private information, $\inf T(p) = 0$. In contrast, sub-samples whose observables would prevent them from purchasing insurance tend to involve larger estimates of the minimum pooled price ratio, which suggests the frictions imposed by private information form the boundary of the existence of insurance markets.
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 $j = 1, \ldots, 8$. 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 re-constructs the analysis in Figure IV using job loss instead of unemployment. I define job loss as an indicator for being laid off or fired from the job held in the previous wave of the survey. The figure present coefficients from separate regressions of leads and lags of the log change in food expenditure on an indicator of job loss, along with controls for year indicators and a cubic in age. Sample is restricted to household heads who did not lose their job in $t-1$ or $t-2$. 
Notes: This figure presents the estimated coefficients of a regression of leads and lags of log household income on an indicator for unemployment. The figure replicates the sample and specification in Figure IV (Panel B) by replacing the dependent variable with log household income as opposed to the change in log food expenditure. I restrict the sample to household heads who are not unemployed in $t-1$ or $t-2$. 
Notes: This figure presents the estimated coefficients of a regression of leads and lags of log household consumption expenditure on an indicator for unemployment. The figure replicates the sample and specification in Figure IV (Panel B) by replacing the dependent variable with log total consumption expenditure on a sample beginning in 1999, surveyed every two years. I restrict the sample to household heads who are not unemployed in \( t - 2 \) or \( t - 4 \). Following the specification in Figure IV (Panel B), the sample is restricted to observations with less than a threefold change in consumption expenditures. Post 1999, the PSID asks a broader set of consumption questions but is conducted every two years, which prevents analyzing total 1-year interval responses to unemployment.