

Knowledge of Future Job Loss and Implications for Unemployment Insurance

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Abstract

This paper studies the positive and normative implications of individuals' knowledge about their potential future job loss. Using information contained in subjective probability elicitation, I show individuals have significant information about their chances of losing their job conditional on a wide range of observable information insurers could potentially use to price the insurance. I derive lower bounds that suggest individuals would need to be willing to pay at least a 75% markup in order to generate the existence of a private unemployment insurance market, far exceeding willingness-to-pay estimates. I derive semi-parametric point estimates of this markup in excess of 300%. This suggests private information about future job loss provides a micro-foundation for the absence of a private unemployment insurance market.

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 social insurance is valuable not only as insurance against the event of becoming unemployed, but also as insurance against learning about potentially becoming unemployed. Hence previous estimates may under-state the value of social insurance. I provide several new methods to use the behavioral response to learning about future job loss to identify the value of unemployment insurance, which generally yield higher estimates than previous literature.

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1 Introduction

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

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

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

I begin by developing the argument that private information prevents the existence of a private UI market. I provide a theory for when a UI market can exist and use the model to derive the empirical estimands of interest. Individuals may have private information about their future unemployment prospects, and insurance may increase their likelihood of unemployment through a moral hazard problem. 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

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

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>).

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

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

of those with higher probabilities of unemployment adversely selecting their contract.⁵

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

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

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

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

⁵This generalizes the no-trade condition of Hendren (2013b) to allow for moral hazard. This pooled cost depends on the distribution of job loss probabilities but does not depend on the responsiveness of unemployment to UI benefits. The first dollar of insurance provides 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 moral hazard elasticity is useful for characterizing optimal social insurance, it does not readily provide insight into why a private market does not exist.

estimate the evolution of beliefs prior to unemployment (measured in the HRS) and the impact of unemployment on food expenditure in the Panel Study of Income Dynamics (PSID), where the latter largely replicates existing work (Gruber (1997); Chetty and Szeidl (2007)). I show that unemployment leads to roughly 6-10% lower consumption growth. In the HRS, I show that roughly 20% of the information about future unemployment is revealed at the point of 1-year prior to the unemployment measurement; scaling the impact on consumption growth by $1/0.8 = 1.25$ yields an estimate of the causal effect of unemployment on consumption. Assuming a coefficient of relative risk aversion of 2, this suggests individuals are willing to pay no more than a 20% markup for unemployment insurance; a range of robustness tests all yield estimates below 50%, well below the 300% markups individuals would have to be willing to pay to overcome the presence of private information. Private information provides a micro-foundation for why companies do not sell private UI policies.

If knowledge about future unemployment prevents the existence of private UI, how does this affect the calculus of optimal government intervention? Returning to the theoretical model, I characterize the optimal unemployment benefits for a utilitarian planner. While the canonical welfare formulas measure the consumption-smoothing benefits of UI using the causal effect of unemployment on the marginal utility of consumption (Baily (1976); Chetty (2008); Landais (2015)), such measures are no longer sufficient when individuals learn ex-ante about future unemployment prospects. Intuitively, UI insures not only against the realization of unemployment, but also against the *realization of information* about future unemployment. This value of UI is missed by previous literature focusing on the impact of the realization of unemployment.

I provide two methods for identifying the value of insurance against the ex-ante realization of knowledge about future unemployment. First, I show that in response to learning about future job loss, spouses are more likely to enter the labor market. A 10pp increase in the probability of becoming unemployed in the next year increases spousal labor supply by 2.5-3%.⁶ Normatively, one can compare these responses to an extensive margin spousal labor supply semi-elasticity to derive the ex-ante markup individuals would be willing to pay for UI. A semi-elasticity of 0.5 (Kleven et al. (2009)) suggests individuals would be willing to pay a 60% markup to obtain insurance against learning one would become unemployed.

Second, I document that consumption responds to learning about future unemployment.

⁶This relates to existing literature documenting the “added worker” effect of spousal unemployment, but suggests part of the spousal response occurs before the onset of unemployment.

Such identification is not straightforward because the HRS – which contains subjective probability elicitation – does not contain information on consumption at the time the elicitation is provided. I extend the two-sample IV strategy used to estimate the causal effect of unemployment on consumption to estimate the causal effect of knowledge about future unemployment on consumption. Using the PSID, I show that in response to unemployment in period t , consumption drops by 2.5% in year $t-1$ relative to $t-2$, even amongst those who remain employed in both previous years. Using the HRS, I show that the impact of unemployment in period t increases the beliefs about future unemployment by 10pp in year $t-1$ relative to year $t-2$. Scaling the 2.5% consumption drop by the amount of information revealed in year $t-1$ relative to $t-2$ (10%) suggests fully learning about unemployment leads to a 25% ex-ante consumption drop prior to becoming unemployed.⁷ Scaling by a coefficient of relative risk aversion of 2, this approach suggests individuals are ex-ante willing to pay at least a 50% markup for unemployment insurance.

Finally, I show that the socially optimal UI benefit level equates a weighted average of the ex-ante and ex-post willingnesses to pay for UI to the aggregate fiscal externality. In general, the ex-ante consumption responses to information are larger than the responses to the onset of unemployment. This suggests previous literature has under-stated the social value of UI by ignoring its value in providing insurance against the realization of information about future unemployment.

Related literature This paper is related to a growing strand of literature studying the degree to which individuals are insured against unemployment and income shocks, and the positive and normative impact of government policy responses.⁸ 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

⁷Note this response is measured within the set of employed individuals, and hence is less likely to suffer bias from state-dependent utility or the fact that individuals may have more time for home production when unemployed.

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).

(2013b) by estimating theoretically-motivated properties of beliefs while simultaneously allowing the elicitation 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 elicitation 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.⁹ Because unemployment involves not only a drop in mean income but also an increase in variance, the large ex-ante responses documented here are consistent with precautionary responses to uncertainty shocks, as in Bloom (2009).¹⁰

This paper also contributes to the growing literature documenting the impact of private information on the workings of insurance markets. Relative to this literature that often focuses on estimating adverse selection of existing contracts, it suggests previous 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.

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

⁹See, Barceló and Villanueva (2010); Bloemen and Stanca (2005); Carroll et al. (2003); Carroll and Samwick (1998, 1997); Dynan (1993); Engen and Gruber (2001); Guariglia and Kim (2004); Guiso et al. (1992); Hubbard et al. (1994); Lusardi (1997, 1998); Stephens (2001).

¹⁰The findings of the spousal labor supply response is also related to the large literature studying the “added worker hypothesis” whereby spouses enter the labor market in response to unemployment shocks. See, for example, Lundberg (1985); Maloney (1991); Gruber and Cullen (1996). My results suggest a portion of the impact of unemployment on spousal labor supply may occur in response to beliefs about future unemployment prior to its actual event.

2 Data

The analysis primarily draws upon data from the Health and Retirement Study (HRS); portions of the analysis, especially those utilizing the food expenditure response to unemployment, will use the Panel Study of Income Dynamics (PSID).

2.1 HRS

I use data from all available waves of the Health and Retirement Study (HRS) spanning years 1992-2013. The HRS samples individuals generally over 55 and their spouses (included regardless of age).¹¹ Table I presents the summary statistics for the main variables and samples used in the analysis.

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

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 (~ 2 years prior). If not, respondents are asked when and why they left their job (e.g. left involuntarily, voluntarily/quit, or retired). To most closely align with the wording of the subjective probability elicitation, I define becoming unemployed as involuntarily losing one’s job in the subsequent 12 months following the previous survey date,

¹¹Despite its focus on an older set of cohorts, the HRS is a natural dataset choice because it contains information on unemployment, consumption, a wide range of observable characteristics insurers use in other markets to price policies, and, most importantly, subjective probability elicitations about future unemployment.

and I exclude voluntary quits and retirement. 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 consider robustness analyses to other definitions of job loss. I construct a measure of job loss in the 6-12 months following the survey. This removes cases where the individuals knew about an immediately impending job loss that could potentially be circumvented by an insurer imposing a waiting period on the insurance policy. I also construct measures of job loss in the 6-24 month window, and measures of whether the individual is unemployed in the subsequent survey round (roughly 24 months after the previous survey).

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

Public Information Estimating private information requires specifying the set of observable information insurers could use to price insurance policies. The data contain a very rich set of observable characteristics that well-approximate variables used by insurance companies in disability, long-term care, and life insurance (Finkelstein and McGarry (2006); He (2009); Hendren (2013b)) and also contain a variety of variables well-suited for controlling for the observable risk of job loss. The baseline specification includes a set of these job characteristics including job industry categories, job occupation categories, log wage, log wage squared, job tenure, and job tenure squared, along with a set of demographic characteristics (census division dummies, gender dummies, age, age squared, and year dummies).¹²

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,

¹²This 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.

heart attack, stroke, lung disease, cancer, high blood pressure, and arthritis) and linear controls for bmi.¹³ 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. By changing the set of observable characteristics, the empirical results allow one to understand how the potential for adverse selection varies with the underwriting strategy of the potential insurer.

Spousal Labor Supply I define spousal labor supply for married households. As the analysis below will focus on changes in spousal labor supply, I restrict the analysis using spousal labor supply to households married in both the current and previous wave of the survey. Spousal labor supply is defined as an indicator for the spouse working for pay in the current wave of the survey. I define labor market entry by the spouse as an indicator for the spouse working for pay in the current wave of the survey and not working for pay in the previous wave of the survey (2 years prior).

Samples I begin with a sample of everyone under 65 currently holding a job who is asked the subjective probability elicitation question, Z . I keep only those respondents who have non-missing job loss responses in the subsequent wave, U , and those with non-missing observable characteristics, X . I exclude the self-employed and those employed in the military.

Table I presents the summary statistics of the samples used in the paper. There are 26,640 observations in the sample, which correspond to 3,467 unique households. The average age is 56 and roughly 40% of the sample is male. Because the HRS primarily focuses on an older population, the mean age in the sample is 56. I present evidence below that the patterns are actually quite stable across the age ranges I can observe. Mean yearly wages are around \$36,000 in the baseline sample and average job tenure is 12.7 years.

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

¹³As shown in Panel 2 of Table 1, 22,831 observations of the 26,640 baseline observations report non-missing values for these health variables.

rationale for treating these elicitations as noisy and potentially biased measures of true beliefs, as is maintained throughout the empirical analyses below.

Finally, for the spousal labor supply response estimation in Section 7, I consider the subsample of respondents who are married in the current and previous wave. This 11,049 observations from 2,214 households. Roughly 70% of spouses are working for pay and 4% of spouses go from not working to working between the previous and current wave of the survey (corresponding to a 2 year gap).

2.2 PSID

While the HRS provides subjective probability elicitations, it does not provide high quality data on consumption patterns. As a result, many papers studying optimal unemployment insurance have used the PSID to measure the impact of unemployment on consumption (Gruber (1997); Chetty and Szeidl (2007)). Following these, I utilize the PSID sample containing data on food consumption for years spanning 1971-1997. I restrict the sample to heads of household between the ages of 25 and 65 who have non-missing food expenditure and employment status variables. I define food expenditure as the sum of food expenditure in the home and out of the home, plus food stamps.¹⁴ Following Gruber (1997), I restrict the 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.

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

¹⁴To compute food stamp expenditure, I follow previous literature and use the response to the monthly food stamp amount multiplied by 12. Results for the impact on consumption in $t - 2$ relative to $t - 1$ are robust to alternative measures of food stamps, such as using the annual measures. However, the size of the consumption drop upon unemployment is larger when using the annual food stamp expenditure question instead of the monthly response multiplied by 12.

3 Theory

I consider a theoretical model of unemployment risk. The goal of the model is to derive the estimands that will form the basis of the empirical work to characterize when a private market can exist and to characterize the ex-ante (utilitarian) optimal level of social insurance. The model will contain both private information (which will create a wedge between what private markets and the government can achieve in terms of allocations) and moral hazard (which implies full insurance is not necessarily socially optimal).

3.1 Setup

There exists a unit mass of currently employed individuals indexed by an unobservable type $\theta \in \Theta$. While θ is unobserved, individuals have observable characteristics, X , that insurers could potentially use to price insurance contracts. Individuals face a potential of losing their job, which occurs with probability p . Individuals of type θ choose consumption in the event of being employed, consumption in the event of being unemployed, the probability of losing their job, p , and a range of other actions, a , that can include items like future consumption, labor effort, and spousal labor supply. These choices are made subject to a choice set $\{c_e, c_u, p, a\} \in \Omega(\theta)$ which may vary across types and be shaped by existing forms of formal and informal insurance. Individuals have increasing and concave utility functions over consumption in the state of being unemployed, $u(c)$, and the state of being employed, $v(c)$, which may differ to allow for state dependent utility, and a (separable) utility function $\Psi(1 - p, a; \theta)$ over other choices, a , and the probability of being employed, p .¹⁵

In addition, there may or may not exist an insurance policy that pays b in the event of being unemployed at a premium of τ paid in the event of being employed. 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.¹⁶ The aggregate utility of an insurance policy (b, τ) is given by

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

¹⁵For simplicity, I assume the functions v and u are common to all types; this will be useful in the empirical application of the welfare analysis in Part II, but is not critical for Part I.

¹⁶Individuals choose c_e and c_u after knowing b and τ , so that one could equivalently think of the individual as choosing consumption. Modeling the insurance contract in this manner removes the need to explicitly model the set of constraints, $\Omega(\theta)$.

There are two key frictions in the model. First, individuals have private information about their types, θ , 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.¹⁷

Part I makes the argument that individuals' private information about future job loss (i.e. heterogeneity in θ unobserved to an insurance company) prevents the existence of a private UI market. In light of this micro-foundation for the absence of private market, Part II studies the socially optimal choice of b and τ .

3.2 The Absence of a Private UI Market: A No Trade Condition

When can a private market profitably sell a private insurance policy, (b, τ) ? Consider a policy that provides a small payment, db , in the event of being unemployed and is financed with a small payment in the event of being employed, $d\tau$, offered to those with observable characteristics X . By the envelope theorem, the utility impact of buying such a policy will be given by

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

which will be positive if and only if

$$\frac{p(\theta) u'(c_u(\theta))}{(1 - p(\theta)) v'(c_e(\theta))} \geq \frac{d\tau}{db} \quad (2)$$

The LHS of equation (2) is a type θ 's willingness to pay (i.e. marginal rate of substitution) to move resources from the event of being employed to the event of being unemployed.¹⁸ The RHS of equation (2), $\frac{d\tau}{db}$, is the cost per dollar of benefits of the hypothetical policy.

Let $\bar{\Theta}(\frac{d\tau}{db})$ denote the set of all individuals, θ , who prefer to purchase the additional insurance at price $\frac{d\tau}{db}$ (i.e. those satisfying equation (2)) who have observable characteristics X . An

¹⁷To see this, consider the case when $\Psi(1 - p, a; \theta)$ is convex in $1 - p$ so that the choice of p by type θ 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 Ψ with respect to $1 - p$, evaluated at the individual's optimal allocation. Intuitively, the marginal cost of effort to avoid unemployment is equated to the benefit, given by the difference in utilities between employment and unemployment. Note that different types, θ , may have different underlying probabilities, $p(\theta)$, that satisfy equation the first order condition.

¹⁸Note 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.

insurer's profit from a type θ 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

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

where the first term is the amount of premiums collected, the second term are the benefits paid out, and the third term is the impact of offering additional insurance on the cost of providing the baseline amount of insurance. Additional insurance may increase the cost through increased probability of unemployment, $dE[p(\theta)] > 0$.¹⁹ But, for the first dollar of insurance, the moral hazard cost to the insurer is zero because $\tau = b = 0$. This insight, initially noted by Shavell (1979), suggests moral hazard does not affect whether insurers' first dollar of insurance is profitable – a result akin to the logic that deadweight loss varies with the square of the tax rate.

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

$$\frac{d\tau}{db} \geq \frac{E \left[p(\theta) \mid \theta \in \bar{\Theta} \left(\frac{d\tau}{db} \right) \right]}{E \left[1 - p(\theta) \mid \theta \in \bar{\Theta} \left(\frac{d\tau}{db} \right) \right]} \quad (3)$$

If inequality (3) does not hold for any possible price, $\frac{d\tau}{db}$, then providing private insurance will not be profitable at any price. The market will unravel a la Akerlof (1970).

A couple simplifications on the model environment facilitate a clearer expression of inequality (3). First, I assume that the mapping from types, θ , to probabilities, $p(\theta)$, is one-to-one so that there is no variation in marginal utilities conditional on $p(\theta)$. Hence a type θ 's willingness to pay for an additional unit of insurance (LHS of equation (2)) will not vary conditional on p and can be written $\frac{p}{1-p} \frac{u'(c_u(p))}{v'(c_e(p))}$ without loss of generality. Second, I assume that this willingness to pay, $\frac{p}{1-p} \frac{u'(c_u(p))}{v'(c_e(p))}$, is increasing in p – that is, those with higher probabilities are willing to pay more for insurance that pays when unemployed. Under these assumptions, 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 $p(\theta)$. Notationally, let P denote the random variable corresponding to the distribution of probabilities chosen in the population in the status quo world without a private unemployment

¹⁹To incorporate observable characteristics, one should think of the expectations as drawing from the distribution of θ conditional on a particular observable characteristic, X .

insurance market, $b = \tau = 0$.²⁰ Equation (3) can be re-written as:

$$\frac{u'(c_u(p))}{v'(c_e(p))} \leq T(p) \quad \forall p \quad (4)$$

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 (2013b). The market can exist only if there exists someone who is willing to pay the markup imposed by the presence of higher risk types adversely selecting her contract. Here, $\frac{u'(c_u(p))}{v'(c_e(p))} - 1$ is the markup 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.

In the case when there are two types θ with different willingnesses to pay but the same probability of unemployment, types do not map 1-1 into $p(\theta)$, and equation (3) does not summarize the no trade condition. However, Appendix A.1 shows that there exists a mapping, $f(p)$, from a subset of $[0, 1]$ into the type space, Θ , such that the no trade condition reduces to testing

$$\frac{u'(c_u(f(p)))}{u'(c_e(f(p)))} \leq T(p) \quad \forall p \quad (5)$$

Hence, the pooled price ratio continues to be a key measure for the frictions imposed by private information even in the presence of multi-dimensional heterogeneity.²¹

Minimum and average $T(p)$ What statistics of $T(p)$ are desired for estimation? The no trade condition in equation (4) must hold for all p . Absent particular knowledge of how the willingness to pay for UI varies across p , it is natural to estimate the minimum pooled price

²⁰In other words, the random variable P is simply the random variable generated by the choices of probabilities, $p(\theta)$, in the population.

²¹Appendix A discusses the generality of the no trade condition. Appendix A.3 illustrates that while in principle the no trade condition does not rule out non-marginal insurance contracts (i.e. b and $\tau > 0$), in general a monopolist firm’s profits will be concave in the size of the contract; hence the no trade condition also rules out larger contracts. Appendix A.2 also discusses the ability of the firm to potentially offer menus of insurance contracts instead of a single contract to screen workers. Hendren (2013b) considers this more general case with menus in a model without moral hazard and shows that when the no trade condition holds, pooling delivers weakly higher profit than a separating contract. In Appendix A.2, I show that a version of the present model without the multi-dimensional heterogeneity can be nested into that model. I also discuss potential theoretical directions for future work studying the robustness of the no trade condition in equations (4) and (5).

ratio, $\inf T(p)$, as in Hendren (2013b). If no one is willing to pay this minimum pooled price ratio, then the market cannot exist.²²

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), the price of adverse selection imposed on a potential market entrant could be higher and depend on other properties of the pooled price ratio. This can motivate the average pooled price ratio, $E[T(p)]$, as a complementary statistic for studying the degree of potential adverse selection.

To see this, suppose an insurer seeks to start an insurance market by randomly drawing an individual from the population and, perhaps through some market research, learns exactly how much this individual is willing to pay. Let's say this person has a probability p of becoming unemployed and for simplicity assume the mapping from types to p is one-to-one. The insurer offers a contract that collects \$1 in the event of being employed and pays an amount in the unemployed state that makes the individual perfectly indifferent to the policy. Then the insurer tries to sell this policy to the marketplace; clearly, all risks $P \geq p$ will choose to purchase the policy as well. Therefore, the profit per dollar of revenue will be

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

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

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

If the insurer is randomly choosing contracts to try to sell, it is not the minimum pooled price ratio that determines profitability. Rather, on average, individuals would have to be willing to pay the pooled price ratio, $E[T(P)]$. In this sense, the average pooled price ratio provides guidance on the frictions imposed on a potential insurance company entrant that would attempt to set up a market through experimentation. From a more practical standpoint, Section 4

²²Although not a necessary condition, the no trade condition will hold if

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

so that absent particular knowledge about how the willingness to pay varies across p , the minimum pooled price ratio provides guidance into the frictions imposed by private information.

will illustrate that one can construct lower bounds on $E[T(p)]$ under weaker assumptions than are required to estimate the minimum pooled price ratio. Hence, it will be useful to have in mind the theoretical relationship between $E[T(p)]$ and the barriers to trade imposed by private information.

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 documenting the relationship between the subjective probability elicitations, Z , and subsequent unemployment, U , conditional on the observable demographic and job characteristics, X . To illustrate the predictive content in the elicitations, 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 vertical axis reports these coefficients. The horizontal axis presents the mean value of the elicitations in each bin. 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 provide information on the pooled price ratio, $T(p)$. To relate the predictive content in the elicitations to the frictions it can impose on the workings of an insurance market, one can proceed in several steps. First, consider the predicted values

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

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

Remark 1. (Hendren (2013b)) Suppose (a) elicitations contain no more information about U than does P : $\Pr\{U|X, Z, P\} = \Pr\{U|X, P\}$ and (b) true beliefs are unbiased $\Pr\{U|X, P\} = P$. Then true beliefs are a mean-preserving spread of the distribution of predicted values:

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

The predicted values, P_Z , present a distributional lower bound on the true distribution of beliefs in the population – the true distribution is more dispersed than the observed distribution of predicted values.

Figure II, Panel B constructs the distribution of the predicted values of $P_Z - \Pr\{U|X\}$. To construct this figure, I use a probit specification²³ 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.

If individuals had no private information, the distribution in Figure II, Panel B, would be statistically identical to a point mass at 0. While there is a large mass of risks with very low predicted probabilities of unemployment, there is an “upper tail” of predicted probabilities lying above the mass of low-risks. In order to start a profitable insurance market, the mass of low-risks would need to be willing to pay a large enough markup to cover the costs of these higher risks.

To understand how much of a markup these higher risks may impose, I extend some results initially derived in Hendren (2013b). For expositional simplicity, consider a particular observable characteristic, $X = x$ and define $m(p) = E[P - p|P \geq p]$ to be the mean residual life function of the distribution P for those with $X = x$. Intuitively, $m(p)$ asks “how much worse are the worse risks than p ?” Of course, $m(p)$ is not observed without observing the true distribution of P . But, one can construct a sample analogue of $m(p)$ using the distribution of predicted values, P_Z :

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

Hendren (2013b) shows that the average value of $m_Z(P_Z)$ generates a lower bound on the average value of $m(P)$:

$$E[m_Z(P_Z)] \leq E[m(P)] \tag{7}$$

Therefore, one can use the observed distribution of the predicted values, P_Z , to generate a lower bound on the extent to which worse risks would impose costs on lower risks if a market were started. With heterogeneous values of X , equation (7) will hold for each value of X (and thus it will hold in expectation as well).

Proposition 1 goes one step further by using the distribution of predicted values to form a lower bound on the average pooled price ratio, $E[T(P)]$.

²³Results 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 .

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

$$E[T(P)] - 1 \geq E[T_Z(P_Z) - 1] \quad (8)$$

where

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

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

The extent to which the average pooled price ratio, $E[T(p)]$, exceeds 1 is bounded below by the ratio of $E[m_Z(P_Z)]$ and $\Pr\{U\}$. Intuitively, $E[m_Z(P_Z)]$ provides a lower bound on the extent to which risks have higher probabilities than p , so that the ratio relative to the mean probability, $\Pr\{U\}$, provides a lower bound on the average pooled cost that one would have to pay to cover the cost of the higher risks.

Table II presents the results.²⁴ 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% (i.e. $E[T(P)] \geq 1.7682$). Adding health controls changes this slightly to 72%; dropping the job characteristic controls increases this slightly to 80%. The presence of such markups impose significant barriers to the existence of a private insurance market for UI.

Figure III (Panel A) presents the results graphically for the specifications with alternative control variables (X) against the psuedo-R squared of the model for $\Pr\{U|X, Z\}$. As one can see, 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. Intuitively, the additional job characteristics controls help better predict unemployment entry rates across,

²⁴As in Hendren (2013b), the construction of $E[T_Z(P_Z)]$ and $E[m_Z(P_Z)]$ is all performed by conditioning on X . To partial out the predictive content in the observable characteristics, I first construct the distribution of residuals, $P_Z - \Pr\{U|X\}$. I then construct $m_Z(p)$ for each value of X as the average value of $P_Z - \Pr\{U|X\}$ above $p + \Pr\{U|X\}$ for those with observable characteristics X . In principle, one could estimate this separately for each X ; but this would require observing a rich set of observations with different values of Z for that given X . In practice, I follow Hendren (2013b) and specify a partition of the space of observables, ζ_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.

say, industry and occupation groups; but it does not remove the thick upper tail illustrated in Figure II, Panel B.²⁵

Adding further controls does not appear to significantly modify the frictions imposed by private information, nor does it significantly alter the R-squared of the model. Controlling for health information does not meaningfully change the estimates, nor does adding additional controls for their work history such as controls for indicators for being employed in the previous two survey waves, as indicated by the “Demo, Job, History” specification. Conversely, dropping the demographic variables such as region, year, gender etc and solely using age and age squared leads to a similar magnitude of private information relative to the baseline specification. Intuitively, the friction imposed by private information is not so much driven by variation in mean odds of becoming unemployed, but rather the thick upper tail of personally-specific knowledge that an individual may have that he or she has a particular chance at losing his or her job.

To illustrate the difficulty faced by a potential insurer in removing the information asymmetry, Figure III, Panel B adds individual fixed effects to a linear specification for $\Pr\{U|X, Z\}$.²⁶ Of course, such fixed effects would be impossible for an insurer to use – an econometrician can view the fixed effects as nuisance parameters that drop out in a linear fixed effects model; in contrast, an insurer must view them as a key input into their pricing policy.²⁷ Adding these fixed effects significantly increases the R^2 of the model, but individuals would still on average have to be willing to pay at least a 40% markup to cover the pooled cost of worse risks. Relatedly, while the autocorrelation in Z across waves is around 0.25, there exists significant predictive content within person, which is consistent with the individual’s elicitation containing largely personal and time-varying knowledge about future job loss.

Population Heterogeneity While on average the markups individuals would have to be willing to pay to start a private UI market are high, a natural question to ask is whether there

²⁵Appendix 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%.

²⁶I use the linear specification so that the residuals, $P_Z - \Pr\{U|X\}$ are well identified and do not suffer bias from the inability to consistently estimate the nuisance parameters. Appendix Table I, Column (2) illustrates that the baseline value for $E[T_Z(P_Z)] - 1$ is 0.6802 (s.e. 0.051) when using the linear specification for $\Pr\{U|X, Z\}$ as opposed to the baseline value of 0.7687 using the probit specification. Hence, a small amount of the attenuation illustrated in Figure III, Panel B (where the fixed effects specification yields 0.40) for the fixed effects estimates relative to the baseline is driven by the specification change from probit to linear.

²⁷Moreover, 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.

are certain subsets of the population for which these would be lower. Columns (4)-(9) of Table II and Figure III, Panels C-F present the estimates of $E[T(P)] - 1$ for various subsamples of the data. Panels C and D of Figure III illustrate the presence of a large amount of private information across all industries and occupational subgroups, with lower bounds on $E[T(P)]$ that all exceed 50%.

The presence of significant amounts of private information about future job loss also spans the age spectrum in the data (45-65), as shown in Columns (4)-(5) of Table III and Panel E of Figure III. Columns (6)-(7) of Table II splits the sample by below and above-median wage workers and continues to find consistent evidence of private information across these subgroups, with lower bounds of 65% and 95%. Appendix Figure I, Panels A and B illustrates the consistency of private information across all years and across all census divisions in the U.S.

One underwriting strategy that has been common in other insurance markets is to limit the insurance market to “good risks”. For example, health-related insurance markets generally exclude those with pre-existing conditions. Hendren (2013b) shows this is consistent with those risks having private information but healthy individuals not.²⁸

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 varying subsamples with different job tenure and 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.

²⁸Loosely, 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 The results suggest high markups imposed by private information on a hypothetical insurance market that pays \$1 in the event of becoming unemployed in the subsequent 12 months. One alternative market – which would be consistent with insurance policies in other contexts – would be to impose waiting periods of, for example, 6 months before the insurance goes into effect. Indeed, if the private information is primarily about knowing that one will lose their job next week, then excluding next week from the insurance contract payouts could remove the informational asymmetry.

In Appendix Table I, I consider an alternative definition of U that excludes those who become unemployed in the first 6 months after the survey. I continue to use the same elicitation, Z , in the construction of the distribution of predicted values. This is appropriate because Z can still satisfy the assumptions in Remark 1 for the alternative measure of U ; but is likely to be a noisier measure of the individual’s true beliefs about losing his or her job in the 6-12 months after the survey, as opposed to the 0-12 months after the survey, as is prompted in the elicitation. Hence, one might expect lower values for $E [T_Z (P_Z)]$ because of this additional measurement error, but it remains a lower bound for the true markup that would be imposed by the presence of private information for an insurance contract that paid db in the event of unemployment with a 6-month waiting period.²⁹

In practice, the results imply a lower bound on $E [T (P)] - 1$ of 0.579 ($p < 0.001$) for a market that imposes a 6-month waiting period. This suggests the frictions imposed by private information cannot be removed through the imposition of waiting periods.

Another strategy could be to require individuals to also file for unemployment insurance with the government.³⁰ Such a practice could impose higher take-up hurdles and also help mitigate claims from job loss events that don’t lead to significant periods of unemployment. To assess the potential barriers to trade imposed by private information in such a market, I construct an outcome that is the interaction of unemployment with whether or not the individual receives government UI benefits. Appendix Figure I, Panel C plots the estimated lower bounds, $E [T_Z (P_Z)] - 1$, for such a hypothetical market. Restricting to government UI for a 0-12 month

²⁹I also abstract from the ability of an individual to change the timing of their unemployment. Such claim timing could impose additional adverse selection costs. In principle, if such timing responses are costly to the worker, they would be a behavioral response that would not affect the insurer’s costs for the first dollar of insurance when $b = \tau = 0$. But, this could be an additional cost factor with non-marginal contracts, as has been noted in other market contexts such as dental insurance (Cabral (2013)).

³⁰Indeed, this is part of the strategy taken by the most recent attempt at providing unemployment insurance by Income Assure.

contract has a lower bound on the average markup of roughly 95%. The figure also illustrates that the implicit markups remain high for other potential timelines, such as 0-24 and 6-24 month payout windows. Restricting insurance payouts to cases in which the individuals filed government UI benefits would not appear to significantly reduce the barriers to trade imposed by private information.

Overall, the results document significant lower bounds on the average markups individuals would have to be willing to pay in order to cover the pooled cost of worse risks. They generally exceed 50% across a wide set of specifications, subsamples, and controls for observable characteristics. Moreover, these lower bounds are derived solely using the assumptions outlined in Remark 1 that allow the elicitation to be noisy and potentially biased measures of true beliefs. The next section adds additional assumptions about the nature of the measurement error in the elicitation 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 Quantification of $\inf T(p)$

To generate a point estimate for the pooled price ratio, one requires an estimate of the distribution of beliefs, P . To obtain this, I follow Hendren (2013b) by making additional assumptions about the distribution of measurement error in the elicitation. 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 elicitation given true beliefs (i.e. elicitation error) and f_P is the distribution of true beliefs in the population (which can be used to construct $T(p)$ at each p). This is obtained by first taking the conditional expectation with respect to p and then using the assumption that $\Pr\{U|Z, X, P\} = P$.

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

I follow Hendren (2013b) by assuming that $Z = P + \epsilon$, where ϵ has the following structure. With probability λ , individuals report a noisy measure of their true belief P that is drawn from a $[0, 1]$ -censored normal distribution with mean $P + \alpha(X)$ and variance σ^2 . With this specification, $\alpha(X)$ reflects potential bias in elicitation and σ represents the noise. While this

allows for general measurement error in the elicitation, it does not produce the strong focal point concentrations shown in Figure 1 and documented in existing work (Gan et al. (2005)). To capture these, I assume that with probability $1 - \lambda$ individuals take their noisy report with the same bias $\alpha(X)$ and variance σ^2 , but censor it into a focal point at 0, 50, or 100. In particular, if their elicitation would have been below κ , they report zero. If it would have been between κ and $1 - \kappa$, they report 50; and if it would have been above $1 - \kappa$, they report 1. Hence, I estimate four elicitation error parameters: $(\sigma, \lambda, \kappa, \alpha(X))$ that capture the patterns of noise and bias in the relationship between true beliefs, P , and the elicitation reported on the surveys, Z .³¹

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

$$F(p|X) = \tilde{F}(p|\Pr\{U|X\}) \quad (9)$$

where I assume $\tilde{F}(p|q)$ is continuous in q (where $q \in \{0, 1\}$ corresponds to the level of $\Pr\{U|X\}$). This assumes that the distribution of private information is the same for two observable values, X and X' , that have the same observable unemployment probability, $\Pr\{U|X\} = \Pr\{U|X'\}$. Although one could perform different dimension reduction techniques, controlling for $\Pr\{U|X\}$ is particularly appealing because it nests the null hypothesis of no private information ($F(p|X) = 1\{p \leq \Pr\{U|X\}\}$).³²

A key difficulty with using functions to approximate the distribution of P is that much of the mass of the distribution is near zero. Continuous probability distribution functions, such as the Beta distributions used in Hendren (2013b), require very high degrees for the shape parameters

³¹Specifically, the p.d.f./p.m.f. of Z given P is given by

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

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

³²Moreover, it allows the statistical model to easily impose unbiased beliefs, so that $\Pr\{U|X\} = E[P|X]$ for all X .

to acquire a good fit. Therefore, I approximate P as a sum of discrete point-mass distributions.³³ Formally, I assume

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

where α_i are a set of point masses in $[0, 1]$ and ξ_i is the mass on each point mass. I estimate these point mass parameters using maximum likelihood estimation. For the baseline results, I use 3 mass points, which generally provides a decent fit for the data. I then compute the pooled price ratio at each mass point and report the minimum across all values aside from the largest mass point. Mechanically, this has a value of $T(p) = 1$ – as noted in Hendren (2013b), 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.

Results Table III reports the results for the same specifications and samples used in Table II for the lower bound estimates. I estimate a value of $\inf T(p) - 1$ of 3.36 in the baseline specification. This suggests that unless people are willing to pay a 336% 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%, but the frictions imposed by private information are quite large.³⁴ As shown in Appendix Table II and consistent with Figure II (Panel B), I estimate that there is a non-trivial fraction of the sample that has a very high chance of losing their job. The presence of this upper tail of high risks makes it incredibly difficult to profitably sell unemployment insurance.

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).

³³This 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.

³⁴Consistent with the idea that the predicted values are lower bounds on the true distribution of beliefs, the estimated minimum pooled price ratios are all well in excess of the estimated lower bounds, $E[T_Z(P_Z)]$.

Overall, the results suggest private information imposes a significant barrier to the existence of a private unemployment insurance market.

For comparison, Hendren (2013b) uses the same empirical strategy to study whether private information prevents those with pre-existing conditions from being able to purchase insurance in three market settings: Long-Term Care insurance, Life insurance, and Disability insurance. In those settings, the estimated markups are all below 100%: 42% for Life, 66% for Disability, and 83% for Long-Term Care.³⁵ The size of the barrier to trade imposed by private information about future unemployment risk appears to be quite substantial.

5 Private Willingness to Pay

Would individuals be willing to pay these 300%+ markups for UI? This section asks how much of a markup would individuals be willing to pay for unemployment insurance after learning their type, θ . 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 (generally year-over-year growth). But if individuals know about their potential future unemployment 1 year prior, controlling for lagged consumption is endogenous to the unemployment realization. In this sense, the micro-foundation of private information about future unemployment raises concerns about the traditional measurement of the causal effect of unemployment on consumption – a key input into the willingness to pay in equation (4). Here, I provide a two-sample IV strategy for re-scaling of these WTP measures by the degree of information revealed about future unemployment to arrive at an unbiased measure of the WTP for UI.

5.1 Theory

To begin, recall this willingness to pay of a type θ is given by their marginal rate of substitution, $\frac{u'(c_u(\theta))}{v'(c_e(\theta))}$, where $c_u(\theta)$ and $c_e(\theta)$ are the consumption of a type θ in the event he or she is unemployed or employed. As noted by Baily (1976) and Chetty (2006), this willingness to pay for UI depends on the causal impact of the event of unemployment on marginal utilities of consumption. To estimate this willingness to pay, I follow Baily (1976), Gruber (1997), and Chetty (2006) by making the assumption that utility over consumption is state independent,

³⁵Appendix Figure II illustrates this comparison.

$v = u$. Using a Taylor expansion for u' around the consumption when employed, $u'(c) \approx u'(c_e(\theta)) + u''(c_e(\theta))(c - c_e(\theta))$, yields the approximation:

$$\frac{u'(c_u(\theta))}{v'(c_e(\theta))} \approx 1 + \sigma \frac{\Delta c}{c}(\theta) \quad (10)$$

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

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

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

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

where the super-script ‘‘Ex-post’’ indicates that this is the willingness to pay for UI conditional on learning $p(\theta)$.

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

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

To see this, let $v(c_{pre})$ denote the utility from consumption at the time of learning ones' type, θ (and hence $p(\theta)$), which is assumed to be additively separable in the utility function.

This yields the Euler equation:

$$v'(c_{pre}(p)) = pu'(c_u(p)) + (1-p)v'(c_e(p)) \quad (11)$$

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

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

$$E[d\log(c)|U=1] - E[d\log(c)|U=0] = \underbrace{E[\log(c_e) - \log(c_u)]}_{\frac{1}{\sigma} W^{Ex-post}} - \underbrace{(E[\log(c_{pre})|U=0] - E[\log(c_{pre})|U=1])}_{\text{Bias from ex-ante response}}$$

The first term is the causal effect of unemployment on consumption – the term desired for measuring willingness to pay under our current assumptions. The second term is the difference in current consumption in the year prior to the unemployment spell, c_{pre} , between those who subsequently become unemployed and those who do not. If individuals have no knowledge of future unemployment U , then their consumption today should not reflect whether or not they become unemployed in the future. However, if individuals learn they may become unemployed, then they may choose to smooth their consumption so that unemployments' impact on consumption growth will understate its total impact on consumption. In this sense, the micro-foundation for the absence of the private market suggests the traditional approach to measuring the willingness to pay for UI suffers bias from ex-ante behavioral responses.

An IV Strategy To solve the consumption bias, I develop a two-sample IV strategy to scale the estimated impact of unemployment on 1-year consumption growth by the amount of information realized in the 1-year period.³⁶ Under log-linearity assumptions on the relationship between consumption and beliefs, it is straightforward to show³⁷ that

$$E[\log(c_e(\theta)) - \log(c_u(\theta))] = \frac{E[d\log(c)|U=1] - E[d\log(c)|U=0]}{1 - (E[P|U=1] - E[P|U=0])} \quad (12)$$

³⁶An 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 θ , this introduces potential selection bias into the estimated causal effect on consumption. Indeed, Online Appendix Figure V shows that individuals have (albeit small) predictive information about future unemployment 10 years in advance.

³⁷This relies on the approximation that $\log(c_{pre}(p))$ is roughly linear in p . And, assume that c_e and c_u do not vary with p (Appendix D.1 provides the derivation for a case when c_u and c_e vary with p under the assumption that the impact of p is the same on both c_u and c_e). With state-independent utility, note that $c_{pre}(1) = c_u$ and

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

5.2 IV Implementation

I do not observe consumption concurrently with beliefs in the HRS samples. As a result, I estimate equation (12) using a 2-sample IV strategy. I estimate the numerator using consumption patterns in the PSID, largely following previous literature. I estimate the denominator using the subjective probability elicitation and unemployment data from the HRS.

5.2.1 Reduced Form

To estimate the numerator in equation (12), I follow Gruber (1997) and Chetty and Szeidl (2007) by regressing the change in log food expenditure on an indicator for unemployment. Panel 1 of Table IV presents the results for a range of specifications. Consistent with Gruber (1997) and Chetty and Szeidl (2007), the results suggest that the event of unemployment leads to a roughly 6-9% lower food expenditure relative to the previous year. Column (1) reports the results for the full sample. Here, unemployment is associated with a 6.33% lower consumption (s.e. 0.533%). However, to the extent to which household heads were also unemployed in the previous year, it may attenuate the difference in consumption. Column (2) limits the sample to those not unemployed in the year prior to the measurement of unemployment. As expected, the coefficient increases slightly to 0.0761 (s.e. 0.00849). Column (3) adds controls for the log change in household expenditure needs and the change in the number of household members to

$c_{pre}(0) = c_e$, so that $\frac{d \log(c_{pre})}{dp} \approx \log(c_u) - \log(c_e)$. Then,

$$\begin{aligned}
 E[\log(c_{pre})|U = 0] - E[\log(c_{pre})|U = 1] &= E\left[\frac{d \log(c_{pre})}{dp}(p - \bar{p})|U = 0\right] - E\left[\frac{d \log(c_{pre})}{dp}(p - \bar{p})|U = 1\right] \\
 &= \frac{d \log(c_{pre})}{dp}(E[p_t|U = 0] - E[p_t|U = 1]) \\
 &= [\log(c_u) - \log(c_e)](E[p_t|U = 0] - E[p_t|U = 1])
 \end{aligned}$$

the specification in Column (2). Column (4) adds individuals fixed effects to the specification in Column (2). Column (5) limits the sample to those over age 40 to more closely align with the HRS sample for whom the private information is identified. This again yields consumption drops of around 6%.

Following previous literature, the analysis to this point makes a couple of specification decisions whose robustness are explored in Columns (6) and (7). First, Column (6) includes the outliers with more than a threefold change in food expenditure. This increases the coefficient to -0.0951 (s.e. (0.0120)). Second, I defined food expenditure as the sum of monthly food spending in the house, out of the house, and – in addition – any spending that occurred through food stamps. 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 following the questions). Second, the wording of the question could induce differential recall bias between the food stamp and non-food stamp food expenditure measures. The food stamp measures suggest concurrent expenditure for the previous week, whereas the food expenditure measures are geared towards a typical week. Since unemployment is co-incident with rises in food stamp use, this differential bias could lead to an under-stating of the impact of unemployment on food consumption.

To obtain a bound on this potential impact, Column (7) excludes food stamp expenditure from the food expenditure measure. Here, the expenditure drop is much larger (-0.164, s.e. 0.0158), and provides a bound on the size of the average expenditure drop.

Finally, note that the no trade condition in equation (6), the full no trade condition in equation (4) requires comparing the willingness to pay, $\frac{u'(c_u(\theta))}{v'(c_e(\theta))}$, to the pooled price ratio at each value of beliefs, p . It may be possible that people with some belief, p , have a greater ratio of marginal utilities than other types. While a full exploration of the joint distribution of the consumption drop and the likelihood of unemployment would require the joint distribution of the elicitation and consumption, one can explore the potential impact of heterogeneity by looking at the heterogeneity in the distribution of consumption.

To this aim, Columns (7) and (8) report estimates from the quantile regression of changes in log food expenditure on unemployment. Column (7) reports the 10th percentile and Column (8) reports the 90th percentile. As can be seen, unemployment is associated with a greater variance in food expenditure changes. It leads to a 21% drop at p10 and a 3% increase at p90.

First Stage Panel 2 of Table IV presents the estimates of the first stage in the denominator of equation (12). To obtain this, I regress the subjective probability elicitation on an indicator for subsequent unemployment. Even if the elicitation are noisy and biased measures of true beliefs, this can continue to provide an estimate of $E[P|U = 1] - E[P|U = 0]$, as the measurement error is in the dependent variable.³⁸ The estimates suggest a coefficient of 0.197 when regressing the elicitation on the subsequent unemployment indicator, which suggests roughly 80% (s.e. 1.2%) of the uncertainty in unemployment is not known 1 year in advance.

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

Columns (8) and (9) show that this estimate rises to 52.8% for quantiles with the 90th percentile of the consumption drop and is actually negative (-7.8%) for the 10th percentile consumption drop. This suggests that there may be significant heterogeneity in the population's willingness to pay for UI. But, all of these estimates remain well below the estimated 300%+ markups shown in Table III.³⁹ In short, the patterns are consistent with private information being a micro-foundation for the absence of a private unemployment insurance market and potentially present a rationale for government intervention.

³⁸Of course, because P and U are bounded variables, the classical measurement error scenario is only an approximation.

³⁹Formally, this suggests individuals are not willing to pay to overcome the hurdles imposed by private information for additional insurance beyond what is currently provided in the status quo world by the government, their firms, friends and family, and other sources of formal and informal insurance. Indeed, the distribution of beliefs, P , in the status quo world are precisely what is desired for measuring whether a private market for additional unemployment insurance would arise. But, it is also natural to ask whether a private market would arise if the government were to lower the amount of UI it provides.

To address this, Gruber (1997) also explores how this consumption drop varies with the level of government unemployment benefits. Extrapolating to a world where the government provides no unemployment benefits, 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.

6 Optimal UI

If private information prevents the existence of a private UI market, then no one is willing to pay the pooled cost of worse risks in order to obtain additional insurance. Additional UI benefits would not deliver a Pareto improvement – some types θ (e.g. the “good risks”) would be worse off, whereas other types (e.g. the “bad risks”) would be better off.⁴⁰

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

6.1 The Classical Case: No Private Heterogeneity

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

$$\frac{u'}{v'} - 1 \approx \sigma \frac{\Delta c}{c} = FE \quad (13)$$

where the LHS of equation (13) is the markup the individual is willing to pay for UI. Under state independent utility ($u = v$), this is given by the consumption smoothing benefits, $\sigma \frac{\Delta c}{c} = \sigma \frac{c_e - c_u}{c_e}$. The RHS of equation (13) is the fiscal externality, FE , imposed by the behavioral response of individuals to the additional government UI benefits. It is often written as $FE = \frac{\epsilon}{1-p}$ where ϵ is the duration elasticity of unemployment and p is the probability of employment; more generally, the fiscal externality is simply the causal impact of the behavioral response to additional benefits, b , financed by taxes, τ , on the government’s budget constraint (Chetty (2006); Hendren (2013a)).⁴¹

⁴⁰Although 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.

⁴¹This in principle includes impacts from extensive margin entry into unemployment (Feldstein (1978); Topel (1983)), improved wages from increased job match quality (Schneider et al. (2013); Nekoei and Weber (2015)), or fiscal impacts from changes in precautionary savings behavior (Engen and Gruber (2001)) or spousal labor supply (Cullen and Gruber (2000)).

In the absence of a micro-foundation for market non-existence, equation (13) characterizes not only the optimal insurance provided by the government, but also the optimal insurance provided by a competitive market. If $\frac{u'-v'}{v'} > FE$, it would suggest private firms should be able to profitably provide additional insurance. Of course, the presence of private information imposes a wedge, $T(p)$, between what the government and private markets can provide.

6.2 A Modified Baily-Chetty Condition

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

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

subject to the budget constraint

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

where $E[p(\theta)]b$ are the unemployment insurance payments, $E[1 + p(\theta)]\tau$ are the taxes collected from the employed to pay for the unemployment benefits, and $E[N(a(\theta))]$ is a placeholder that captures the net government budget from all other aspects of the individual's behavior (captured in $a(\theta)$).⁴² In contrast to markets, the government need not respect any participation constraint: it can force everyone to pay premiums, τ , so that the budget constraint involves the entire population, as opposed to the adversely selected subset, $\bar{\Theta}(\frac{d\tau}{db})$.

It is straightforward to show that the level of b and τ that maximizes utilitarian welfare solves the modified Baily-Chetty condition:

$$W^{Social} = FE \tag{14}$$

where

$$W^{Social} = \frac{E\left[\frac{p(\theta)}{E[p]}u'(c_u(\theta))\right]}{E\left[\frac{(1-p(\theta))}{E[1-p]}v'(c_e(\theta))\right]} - 1 \tag{15}$$

⁴²I 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.

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.⁴³ The intuition for the difference between equations (14) and (13) is straightforward. The envelope theorem implies individuals value additional benefits using their marginal utilities. The marginal utility of additional benefits to a type with probability $p(\theta)$ 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 individuals are identical in their probabilities of experiencing unemployment (e.g. no one has unique knowledge about the event), then $p = E[p]$, and the formula reduces to the canonical formula in equation (13) with the average utilities $E[u']$ and $E[v']$ in place of u' and v' .

In this sense, canonical willingness to pay measures for UI are identified using the varia-

⁴³To see this, note that the optimal allocation solves the first order condition:

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

where

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

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

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

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

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

So, the optimality condition becomes:

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

where

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

If only p is the margin of adjustment, then

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

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).

tion in consumption resulting from the event of unemployment. But, from a social optimality perspective, UI also serves the role of providing insurance against *knowledge about future unemployment*, $p(\theta)$. While existing methods for valuing UI miss this value of insurance against information, the existence of this ex-ante insurance value provides a new method for valuing additional UI by using ex-ante behavioral responses to knowledge about future unemployment. This will provide a welfare measure of the value of additional UI to those who have been missed in previous estimates and also allow for a valuation of UI that does not require assumptions about the state dependence of utility over consumption when employed and unemployed.

6.3 The Value of Insurance Against Information The Euler Equation and a New Method for Identifying W

If individuals learn about future unemployment before the event occurs, it should effect behavior at the point when they learn (ex-ante relative to the job loss). Theory suggests that these ex-ante and ex-post behaviors are linked through an Euler equation. Let $c_{pre}(p)$ denote the consumption of an individual at the time when learning θ .⁴⁴ For simplicity, assume the mapping from θ to p is 1-1 so that the heterogeneity is fully characterized by p . The individual's choice of how much to consume today relative to saving to consume after the event of unemployment is realized will satisfy an Euler equation (Equation (11)). Consider the subset of people who learn their future unemployment status with certainty, $p \in \{0, 1\}$. From the Euler equation (11),

$$\begin{aligned} v'(c_{pre}(1)) &= u'(c_u(1)) \\ v'(c_{pre}(0)) &= v'(c_e(0)) \end{aligned}$$

Intuitively, those who know they will lose their job One can define the welfare impact of UI across who learn ex-ante about

$$W^{ex-ante} = \frac{v'(c_{pre}(1)) - v'(c_{pre}(0))}{v'(c_{pre}(0))} \approx \frac{d \log(v'(c_{pre}(p)))}{dp} \quad (16)$$

$W^{ex-ante}$ evaluates the willingness to pay across states of the world on the subset of the population that learns with certainty that they will or will not lose their job. It measures the value of moving resources from someone that has learned he or she is less likely to lose his or her job to someone who has learned he or she is more likely to lose his or her job. In this sense, the welfare metric is identified from the subset of the population that has more knowledge about their future unemployment.

⁴⁴Note c_{pre} is captured in the model in Section 2 by thinking of it as an element of a .

Ex-ante versus Ex-post $W^{ex-ante}$ is the markup individuals are willing to pay for insurance against learning they might lose their job, whereas $W^{ex-post}$ is the average markup individuals are willing to pay for insurance against losing one's job conditional on already learning θ . How do these quantities relate to each other?

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

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

The next two sections presents two approaches to identifying ex-ante behavioral responses and estimating $W^{ex-ante}$. The key hurdle is that the HRS does not provide consumption measures concurrently with the elicitation measures, so direct computation of $c_{pre}(p)$ is not feasible. I follow two approaches. First, I estimate the impact on spousal labor supply and estimate the value of social insurance using the intra-temporal tradeoff between labor and leisure and an assumption about the elasticity of spousal labor supply. Second, I estimate equation (18) using a two-sample IV approach that uses the time evolution of knowledge about future unemployment as an instrument for consumption in the PSID (the reduced form) and for beliefs in the HRS (the first stage).

7 Impact on Spousal Labor Supply

When individuals learn they may lose their job, their marginal utility of income should increase. This should not only decrease consumption activities, but also it may increase activities that generate income, such as spousal labor supply. Here, I consider the impact on spousal labor entry into the labor market. Suppose a spouse can enter the labor market to earn $\$y$ at a fixed cost of η , where η is distributed heterogeneously in the population.⁴⁵ At an optimum, all individuals where the marginal utility of that $\$y$ exceeds η will choose to work. Appendix D.2 shows that

$$W^{ex-ante} \approx \frac{d\phi}{dp} \frac{1}{\epsilon^{semi}} \quad (17)$$

where $\frac{d\phi}{dp}$ is the percentage point increase in labor force participation resulting from a 1pp increase in p , and ϵ^{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. By taking the ratio of the impact of learning about unemployment relative to the impact of an increase in wages, equation (17) translates the impact on the labor force participation rate into units of the marginal utility of income.

Results Using the HRS sample of all households with spouses, I define labor market entry by the spouse as an indicator for the spouse working for pay in the current wave of the survey and not working for pay in the previous wave of the survey (2 years prior). I restrict the sample to individuals who are married in both the current and previous wave. Figure IV plots the coefficients on 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.

The figure suggests spouses of those with higher elicitation are more likely to enter the labor force. The pattern is slightly different than for consumption, with labor market entry more likely if the subjective elicitation is quite high. The 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 $Z < 50$,

⁴⁵Spousal labor supply is incorporated into the general model in Section 2 by thinking of it as an element of a .

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. In response to smaller variations in information, individuals adjust consumption; once the chance of job loss crosses a sufficient threshold, spouses become more likely enter the labor market.

Table V provides a linear parameterization of the regression relationship. Column (1) of Table V presents this coefficient, and consistent with the approach for ex-post consumption in Table IV, also includes a control for $Z = 0$. This yields a slope of 0.0273 (s.e. 0.0112). In contrast to the ex-post consumption measures above, the results are robust to dropping the control for focal point elicitation of $Z = 0$, as shown in Column (2). Column (3) restricts the sample to those who do not end up losing their job in the 12 months after the survey, yielding similar results. Column (4) uses a specification that defines spousal work as an indicator for full-time employment, as opposed to any working for pay. This definition counts shifts from part time to full time work as labor market entry, as opposed to transitions to work for any pay. The pattern is largely similar, with a slope of 0.0286 (s.e. 0.0128).

One identification concern about the results 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 (5) 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 0.00792 (s.e. 0.0102) and is not statistically distinct from zero. Column (6) adds household fixed effects to the regression in Column (1) and Column (7) adds individual fixed effects to the specification in Column (1). The point estimates are quite stable, although noisy with the individual fixed effects. Overall, the pattern appears to be consistent with the hypothesis that households respond to learning about unemployment by increasing spousal labor supply.

In addition to impacts on entry, one may also expect to see fewer spouses leave the labor force in response to learning about future unemployment prospects for the other earner. However, one does not find much evidence of this pattern in the data. Column (8) defines labor market exit as an indicator for a spouse working for pay last wave and not working for pay in the current period. In contrast to the idea that spouses would be less likely to choose to enter the labor market, the coefficient of 0.017 (s.e. 0.0116) is positive, although not statistically significant.

One possible explanation for why spouses are not less likely to stop working could be that it's not their own choice; if a husband is likely to lose his job, the same set of circumstances may also affect the ability of the wife to stay in her job. To this aim, Column (9) shows that the elicitation is positively related to spousal unemployment in the subsequent year. 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.

Welfare Panel 2 of Table V presents the estimated values of $W^{ex-ante}$ using equation (17). To do so, I not only divide by the semi-elasticity of labor supply (here assumed to be 0.5), but 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 $\frac{var(Z|X)}{var(P|X)}$, where X are the controls in the regressions of labor force participation on Z .⁴⁶

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, which is not surprising given the stability of the regression coefficient in Panel 1. Moreover, these estimates are lower bounds to the extent to which spousal labor supply is constrained from correlated shocks and to the extent to which $W^{ex-ante}$ is less than the value of insurance on the set that includes those that do not learn about their future unemployment, W .

For comparison, the results from Chetty (2008) that calculate the impact of additional benefits on unemployment duration suggests a value of $FE \approx 0.5$.⁴⁷ Assuming this size of a fiscal externality from additional benefits, the size of the spousal labor supply response suggests additional UI would be preferred from an ex-ante perspective.

Overall, the spousal labor supply response is quite large and indicative of a significant value of social insurance. Moreover, the overall pattern is also consistent with the finding of Gruber

⁴⁶To do so, I construct $var(Z|X)$ as the square of the RMSE of a regression of Z on the control variables. I construct $var(P|X)$ as $var(P|X) \approx cov(Z, L|X)$, where the approximation would hold exactly if the measurement error in Z were classical. To construct $cov(Z, L|X)$, I first residualize L and Z on X and then calculate the covariance of the residuals, then adjust for the degrees of freedom introduced in the initial residualization.

⁴⁷Note this behavioral response is not in terms of the response of probability of unemployment; but the choice of unemployment duration can be thought of as incorporated into other behavioral responses, $a(\theta)$. Later work has found mixed evidence on the impact of UI on wages in various contexts (Schneider et al. (2013); Nekoei and Weber (2015)), which would also be ideally incorporated into these analyses.

and Cullen (1996) that higher levels of social insurance reduce the response of spouses into the labor market in response to unemployment. The presence of greater social insurance reduces the degree to which learning about future unemployment increases the marginal utility of income, which reduces the incentives to enter the labor force. Relative to this literature, I find that a large fraction of these responses occur even before the onset of unemployment.⁴⁸

8 Consumption

In addition to spousal labor supply responses, one would also expect individuals who learn about future unemployment to cut back on their current consumption. Assuming utility over consumption, $v(c_{pre})$, is additively separable from other utility arguments, the ex-ante welfare value of UI is given by

$$W^{ex-ante} \approx \sigma_v \frac{d \log(c_{pre})}{dp} \quad (18)$$

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

As noted above, a key hurdle to identifying these effects is the absence of concurrent consumption measures in the HRS. I follow the approach in Section 5 to use a 2-sample IV approach that uses the information about beliefs in the HRS combined with the information on consumption that is available in the Panel Study of Income Dynamics (PSID). In contrast to the analysis in Section 5 that focused on the amount of information revealed in the 1 year prior to the unemployment measurement, I utilize the variation in beliefs induced by the passage of time between 1 and 2 years prior to the onset of unemployment.

Consumption Patterns in PSID While Section 5 explored the impact of unemployment on concurrent consumption growth, here I step back and explore the pattern of consumption around unemployment spells. For each year I construct the change in log food expenditure relative to the previous year, $g_t = \log(c_t) - \log(c_{t-1})$. Figure VII illustrates how food expenditure growth in year $t + j$, g_{t+j} , relates to the onset of unemployment in year t for $j = -4, \dots, 4$. I regress g_{t+j} on an indicator for unemployment in year t , controlling for a cubic in age and year dummy

⁴⁸As shown in Column (3) of Table V, the response occurs even on the subset of those who find it likely they will lose their job but who do not actually end up losing their job in the 12 months after the survey.

indicators. Panel A reports the pattern for the entire sample. Panel B restricts the sample to those who are not unemployed in years $t - 1$ and $t - 2$.

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

To further explore the robustness of this pattern and quantify the magnitude of the expenditure drop in the 1-2 years prior to unemployment, Table VI presents the results of a regression of the difference in log food expenditure in year $t - 2$ and year $t - 1$, $\log(c_{t-1}) - \log(c_{t-2})$, on an indicator for unemployment in current period. Column (1) includes controls for only age and year dummies, analogous to the specification in Figure VII, Panel A. This shows a -0.0336 (s.e. 0.0057) drop in expenditure in the year before unemployment occurs. Column (2) restricts the sample to those who are not unemployed in years $t - 1$ and $t - 2$, analogous to the specification in Panel B of Figure VII. This attenuates the food expenditure drop slightly to -2.5% (s.e. 0.00942). This is to be expected given the auto-correlation of 0.387 in unemployment status across years in the baseline sample.

An additional concern is that household size or needs change around the time of unemployment. Column (3) of Table VI adds controls for both the change in household size in years $t - 2$ versus $t - 1$ and also the change in expenditure needs, a variable available in the PSID that captures the total needs of the household based on its size and composition.⁴⁹ This delivers a coefficient of -0.0249 (s.e. 0.00994), very similar to the -0.025 (s.e. 0.00942) coefficient in Column (2). Column (4) adds individual fixed effects to the specification in Column (2) and again delivers a coefficient of -0.0231 (s.e. 0.013), close to the -0.025 in Column (2). Column (5) restricts the sample to individuals over age 40 to more closely align with the HRS sample, which yields a coefficient of -0.0287 (s.e. 0.0151). Column (6) expands the sample to include outliers with more than threefold changes in food expenditure, yielding a coefficient of -0.0231 (s.e. 0.0121).

Forward looking behavior versus correlated shocks A key threat to identification of the ex-ante response to unemployment is that individuals are responding not to the knowledge

⁴⁹For some years, the PSID also has food need measures available. Controlling for these reduces the sample size but delivers similar results.

of unemployment but rather to the impact of a correlated event. For example, if unemployment usually occurs after pay reductions at work, one might worry that the food expenditure reductions in period $t - 1$ relative to $t - 2$ are not due to responses of individuals on their Euler equation, but rather are the result of hand-to-mouth consumers responding to changes in income.

To test for this potential concern, Column (7) adds controls for a third degree polynomial of changes in log household income to the baseline specification in Column (2). This yields a coefficient of 0.025 (s.e. 0.00935) nearly identical to the baseline specification in Column (2). Column (8) adds controls for a third degree polynomial of changes in log income of the household head, yielding a coefficient of -0.0248 (s.e. 0.0095).⁵⁰ To understand why the results are not significantly affected by adding controls for income, Appendix Figure V replicates Figure V (Panel B) using log household income as the dependent variable as opposed to log food expenditure. For those employed in both $t - 2$ and $t - 1$, unemployment in period t is not associated with any significant income change in any of the years prior to unemployment.⁵¹ Overall, the results suggest that 1-2 years beforehand, individuals drop their consumption by about 2.5% in response to the future the unemployment event.

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

$$\Delta^{\text{First Stage}} = \underbrace{E[P_{t-1,t}|U_t = 1] - E[P_{t-1,t}|U_t = 0]}_{\text{Knowledge in } t-1 \text{ about } t} - \underbrace{E[P_{t-2,t}|U_t = 1] - E[P_{t-2,t}|U_t = 0]}_{\text{Knowledge in } t-2 \text{ about } t}$$

The first component of $\Delta^{\text{First Stage}}$ is precisely the first stage used in Section 5, and can be obtained by simply regressing the elicitation, Z , on an indicator for unemployment in the subsequent 12 months, U . This yields 0.197 (s.e. 0.0123). In the year prior to unemployment,

⁵⁰The 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.

⁵¹Note 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 average difference in the beliefs, P , for those who subsequently do experience unemployment versus those that do not subsequently experience unemployment is roughly 20pp.

Some of this difference in beliefs was already present in the 2 years prior. To subtract off the value of $E[P_{t-2,t}|U_t = 1] - E[P_{t-2,t}|U_t = 0]$, one would ideally have an elicitation about unemployment in the 12-24 months after the elicitation. However, we can get a lower bound by using the elicitation about the future 12 month unemployment to predict unemployment in the 12-24 months after the survey. The second row of Appendix Table IV reports this coefficient as 0.0937 (s.e. 0.0113). This second data point is also reported in Online Appendix Figure V. Intuitively, people know more about their prospects for losing their job in the next 12 months than in the 12-24 months from now. The results suggest this difference-in-difference in beliefs between the unemployed and employed in years $t - 2$ and $t - 1$ is 0.1031 (s.e. 0.0159), as shown in the first row of Panel 2.⁵²

The next row scales the reduced form coefficients in Panel 1 by the first stage difference in beliefs of 0.1031. For the baseline specification in Column (2) using the sample that are employed in years $t - 2$ and $t - 1$, this yields a value of $\frac{d \log(c_{pre})}{dp} = 0.24$ (s.e. 0.09). This suggests learning one is 10% more likely to lose their job would cause a 2.4% drop in consumption. Scaling this estimate by a coefficient of relative risk aversion of $\sigma = 2$, it implies $W^{ex-ante} = 0.48$ (s.e. 0.18), which suggests individuals would be willing to pay a 48% markup for additional unemployment insurance. The remaining columns use the same first stage estimation to scale the estimates for the other specifications. These results generally fall around 50%. Compared to a value of FE of 0.5, they suggest the current level of unemployment benefits is about optimal provided $W^{Social} \approx W^{ex-ante}$, which is true if consumption, c_u and c_e , are not systematically varying with p . If the value of UI to those that learn about their future unemployment is higher than to those for whom it comes as a complete surprise, then the point estimates would suggest $W > W^{ex-ante} \approx 0.5$, so that additional unemployment insurance benefits would be ex-ante preferred. More generally, one can combine the ex-ante and ex-post measures of willingness to pay to construct a measure of the social willingness to pay that allows those who learn about future unemployment to have a different valuation of unemployment insurance than those who do not learn ex-ante about their potential for losing their job.

⁵²Online Appendix Figure V also reports the coefficients for future years of unemployment and obtains estimates of $E[Z_{t-j,t}|U_t = 1] - E[Z_{t-j,t}|U_t = 0]$ ranging from 0.1 to 0.05 at $j = 8$, which suggests most of the information in Z is about unemployment in the subsequent year. This is consistent with a relatively flat consumption growth profile for years prior to $t - 2$ as shown in Figure V.

9 Ex-ante and Ex-post Welfare

The previous two sections provide measures of the value UI yields by providing insurance against the realization of information about p . Under the assumption that c_u and c_e do not systematically vary with p , then the markup individuals are willing to pay for insurance against p , $W^{ex-ante}$, is the same as the markup individuals would be willing to pay for insurance against the realization of unemployment conditional on beliefs $p(\theta)$, $W^{Ex-ante}$. However, in general the value of insurance against learning one might lose their job could differ from the value of insurance against the realization of the event of unemployment.

The optimality formula characterizing W^{Social} captures both of these values of insurance – the value of insurance against the realization of information, $p(\theta)$, and the value of insurance against the realization of unemployment, U . To the extent to which those with higher values of $p(\theta)$ also have higher marginal utilities of consumption, $u'(c_u)$ and $v'(c_e)$, the value of insurance will exceed $W^{Ex-post}$. Intuitively, a positive covariance between $p(\theta)$ and the marginal utility of consumption indicates that those who learn they may lose their job ex-ante have a higher valuation of unemployment insurance than those who have no ex-ante knowledge.

The social willingness to pay can be approximated as a weighted average of the ex-ante and ex-post willingness to pay. Retaining the assumption of state independence ($u = v$) which is necessary for the construction of $W^{Ex-post}$, we have

$$W^{Social} \approx (1 - (E[P|U = 1] - E[P|U = 0])) W^{Ex-post} + (E[P|U = 1] - E[P|U = 0]) W^{Ex-ante} \quad (19)$$

so that the social WTP is a weighted average of the value of insurance against U conditional on p and the value of insurance against p . The weights are given by the amount of information revealed ex-ante ($E[P|U = 1] - E[P|U = 0]$) and ex-post ($1 - (E[P|U = 1] - E[P|U = 0])$). As noted in Table IV, roughly 20% of uncertainty about U is revealed at a point of 1-year before the potential spell. This suggests that the social willingness to pay in equation (15) is roughly equal to a 20% of $W^{ex-ante}$ and 80% of $W^{ex-post}$.

Table VII presents the results for W^{Social} using the baseline specification assumptions⁵³ in Tables IV-VI and a range of assumptions over the coefficient of relative risk aversion, σ , and the semi-elasticity of spousal labor supply, ϵ^{semi} . For a coefficient of relative risk aversion of 2, the

⁵³In 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).

results suggest an ex-ante willingness to pay a markup of 48.5% against the realization of p but only a 18.9% markup against the realization of U given p . This suggests that the total social value of insurance is 24.8%. Column (4) presents the baseline results using the ex-ante labor supply response to measure the ex-ante willingness to pay for UI. This yields a willingness to pay of 60.2%; combining this with the ex-post willingness to pay of 18.9% yields a total willingness to pay of 27.1%.

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

Overall, the results provide evidence that the ex-ante value of insurance – the component largely ignored in previous literature – is larger than the value of the ex-post insurance against the realization of unemployment. This suggests focusing on the value of ex-ante insurance increases the social value of unemployment insurance.

10 Conclusion

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

This micro-foundation motivates a modification to the formulas characterizing the utilitarian-optimal unemployment insurance benefit level. If individuals learn about unemployment before it actually occurs, they may respond to mitigate the causal effect of unemployment on their marginal utilities of income. I provide evidence that individuals respond by lowering consumption and increasing spousal labor force entry. While this renders traditional welfare analyses that focus on the causal effect of unemployment insufficient for welfare analysis, I illustrate how to use the response to information about future unemployment to estimate the ex-ante value of unemployment insurance.

The approaches can be applied to other settings, such as disability insurance, social security,

and health insurance contexts. In particular, the 2-sample IV procedure developed in Section 5 and 8 shows one can conduct such welfare analysis without necessarily simultaneously observing consumption and beliefs. In this sense, I hope the analyses in this paper provides a path forward for motivating a micro-foundation for government intervention and the calculation of the optimal government intervention.

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ONLINE APPENDIX: Not For Publication

A No Trade Condition

A.1 Multi-Dimensional Heterogeneity

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

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

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

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

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

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

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

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

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

which amounts to testing the no trade condition.

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

A.2 Robustness to Menus

Here, I illustrate how to nest the model into the setting of Hendren (2013b), then apply the no trade condition to rule out menus. Loosely, the present model is effectively the same model as in Hendren (2013b) aside from the introduction of a moral hazard problem and endogenous marginal utilities, u' and v' . I assume here that there is no heterogeneity in the marginal utilities across types and leave future work to study the problem of menus when individuals are making a range of additional choices. With this simplification, the only distinction relative to Hendren (2013b) is the introduction of the moral hazard problem in choosing p . Below, I show that introducing a moral hazard problem can't make trade any easier than in a world where $p(\theta)$ is exogenous and not affected by the insurer's contracts; hence the no trade condition results from Hendren (2013b) can be applied to rule out menus.

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

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

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

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

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

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

condition $\Psi'(\hat{q}(\Delta; \theta); \theta) = \Delta$.

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

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

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

Throughout, I maintain Assumption A.3: that π is concave in (ν, Δ) . Below in Section A.4, I discuss primitives for such concavity.

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

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

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

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

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

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

because insurance causes an increase in p . Now, Hendren (2013b) shows that the no trade condition implies that $\tilde{\Pi} \leq 0$ for all menus, $\{\nu(\theta), \Delta(\theta)\}$. Therefore, the no trade condition also implies $\Pi \leq 0$ for local variations in the menu $\{\nu(\theta), \Delta(\theta)\}$ around the endowment. Combining with the concavity assumption, this also rules out larger deviations.

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

A.3 Concavity Assumptions

Heretofore, I have placed no restrictions on either the nature of the distribution of types, θ , or the structure of the effort function, Ψ . This allows for considerable generality in characterizing when insurance markets can exist with moral hazard and adverse selection. But, the presence of moral hazard in this multi-dimensional screening problem induces the potential for non-convexities in the constraint set. Such non convexities could potentially limit the ability of local variational analysis to characterize the set of implementable allocations. Fortunately, a simple condition ensures that a local variational analysis provides a global characterization of the existence of profitable deviations from the endowment. Intuitively, the needed condition to ensure sufficiency of a local analysis is that the marginal profitability of insurance declines in the amount of insurance provided.

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

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

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

$$\begin{aligned} C_u(x) &= u^{-1}(x) \\ C_v(x) &= v^{-1}(x) \end{aligned}$$

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

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

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

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

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

This assumption requires the marginal profitability of insurance to decline in the amount of insurance provided. If the agents choice of p is given exogenously (i.e. does not vary with Δ), then concavity of the utility functions, u and v , imply concavity of $\pi(\Delta, \mu; \theta)$. Assumption A.3 ensures that the ability of agents to choose p does not induce regions in which the marginal profitability of insurance actually increases in the amount of insurance.

A.4 Sufficient Conditions for Concavity

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

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

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

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

A.4.1 Conditions that imply $\frac{\partial^2 \pi}{\partial \Delta^2} < 0$

Taking the first derivative with respect to Δ , we have

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

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

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

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

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

which is necessarily true whenever

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

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

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

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

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

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

so that

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

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

A.4.3 Conditions to imply $\frac{\partial^2 \pi}{\partial \Delta^2} \frac{\partial^2 \pi}{\partial \mu^2} - \left(\frac{\partial^2 \pi}{\partial \Delta \partial \mu} \right) > 0$

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

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

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

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

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

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

which reduces to the inequality

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

where

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

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

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

A.4.4 Summary

As long as $\Psi''' > 0$ and $\frac{u'(c_u^e)}{v'(c_e^e)} \leq 2$, the profit function is guaranteed to be concave. As noted in the text, generally one finds empirically that $\frac{u'(c_u^e)}{v'(c_e^e)} \leq 2$. Therefore, the unsubstantiated assumption for the model is that the convexity of the effort function increases in p , $\Psi''' > 0$. An alternative statement of this assumption is that $\frac{\partial^2 \hat{q}}{\partial \Delta^2} < 0$, so that the marginal impact of work incentives on the employment probability is declining in the size of the work incentives.

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

B Proof of Proposition 1

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

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

Proof: note that

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

so that

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

So, we wish to show that

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

Note that:

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

And:

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

So, we wish to test whether

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

or

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

or

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

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

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

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

Proof of Proposition.

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

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

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

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

so that

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

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

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

so that

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

which is the desired result.

C Consumption Response of c_u and c_e

C.1 Data

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

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

C.2 Results

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

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

Column (2) reports the results using household consumption instead of household consumption per capita. This yields a coefficient of -0.110 (s.e. 0.0596) on the elicitation for those who do not experience unemployment. Here, the coefficient on the unemployment interaction

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

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

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

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

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

⁵⁴If the pattern reflects selection between high and low income individuals, the covariance calculations for the optimal degree of unemployment insurance would be valid as measuring the benefits from additional UI, but one would want to take into account the impact of UI on the effective total amount of redistribution in the economy and include the associated fiscal externalities akin to the redistributive costs associated with the progressive income tax schedule (Kaplow (2008); Hendren (2014)).

for unemployment status and an indicator for a focal point response of $Z = 0$. For simplicity, I summarize the negative relationship between Z and log consumption expenditure by pooling across unemployment status and do not interact Z with U .

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

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

D Welfare Metrics

D.1 IV Derivation

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

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

so that

$$u''(c_{pre}(p)) \frac{dc_{pre}}{dp} = u'(c_u(p)) - u'(c_e(p)) + pu''(c_u(p)) \frac{dc_u}{dp} + (1-p)u''(c_e(p)) \frac{dc_e}{dp}$$

Now, taking expectations (with respect to θ) and taking a Taylor expansion for u' (ignoring u''' terms, as is common in existing literature) yields

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

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

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

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

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

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

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

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

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

Using the Euler equation yields

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

so that

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

or

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

D.2 Ex-ante labor supply derivation

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

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

where $\eta(\theta)$ is the disutility of labor for type θ , distributed F_η in the population.

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

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

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

Now, note that

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

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

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

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

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

and integrating across all the types p , we have

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

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

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

so,

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

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

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

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

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

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

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

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

This section shows that

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

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

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

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

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

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

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

Similarly,

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

So that

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

and note

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

(think of a regression of p on U). Therefore,

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

Now, Section D.1 shows that the Euler equation implies $\frac{-d \log(c_{post})}{dp} + E[\log(c_e) - \log(c_u)] \approx \frac{-d \log(c_{pre})}{dp}$, so that

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

Additionally, note that

$$\begin{aligned} \frac{E[u'(c_u)]}{E[u'(c_e)]} &\approx 1 + \sigma \frac{\bar{c}_e - \bar{c}_u}{\bar{c}_e} \\ &\approx 1 + \sigma (E[\log(c_e) - \log(c_u)]) \end{aligned}$$

Combining, we have

$$W^{Social} + 1 \approx (1 + \sigma (E[\log(c_e) - \log(c_u)])) \left(1 + \sigma \left[\frac{-d \log(c_{pre})}{dp} - E[\log(c_e) - \log(c_u)] \right] (E[P|U = 1] - E[P|U = 0]) \right)$$

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

$$W^{Social} \approx (1 - (E[P|U = 1] - E[P|U = 0])) \sigma (E[\log(c_e) - \log(c_u)]) + (E[P|U = 1] - E[P|U = 0]) \sigma \frac{-d \log(c_{pre})}{dp}$$

or

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

TABLE I
Sample Summary Statistics

Variable	Panel 1: Baseline Sample		Panel 2: Health Sample		Panel 3: Married Sample	
	mean	std dev	mean	std dev	mean	std dev
<i>Selected Observables (subset of X)</i>						
Age	56.1	5.1	56.1	5.2	56.6	5.0
Male	0.40	0.49	0.41	0.49	0.44	0.50
Wage	36,057	143,883	37,523	154,993	38,138	55,722
Job Tenure (Years)	12.7	10.8	12.7	10.9	13.6	10.9
<i>Unemployment Outcome (U)</i>	0.031	0.173	0.032	0.175	0.029	0.168
<i>Subjective Probability Elicitation (Z)</i>	15.7	24.8	15.7	24.6	14.8	24.0
<i>Spousal Labor Supply</i>						
Working for Pay					0.693	0.461
Fraction Entering					0.039	0.194
<i>Sample Size</i>						
Number of Observations		26,640		22,831		11,049
Number of Households		3,467		3,180		2,214

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

TABLE II
Lower Bound Estimates

Specification:	Alternative Controls			Sub-Samples					
	Baseline (1)	Demo (2)	Health (3)	Age ≤ 55 (4)	Age > 55 (5)	Below Median Wage (6)	Above Median Wage (7)	Tenure > 5 yrs (8)	Tenure ≤ 5 yrs (9)
$E[T_Z(P_Z)-1]$	0.7682	0.8033	0.7198	0.6983	0.8150	0.6513	0.9515	1.0996	0.4759
s.e.	(0.053)	(0.051)	(0.052)	(0.081)	(0.066)	(0.058)	(0.094)	(0.093)	(0.057)
$E[m_Z(P_Z)]$	0.0236	0.0247	0.0228	0.0208	0.0256	0.0244	0.0228	0.0192	0.0270
s.e.	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)
p-value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
$\Pr\{U=1\}$	0.0307	0.0307	0.0317	0.0297	0.0314	0.0375	0.0239	0.0175	0.0568
Controls									
Demographics	X	X	X	X	X	X	X	X	X
Job Characteristics	X		X	X	X	X	X	X	X
Health			X						
Num of Obs.	26640	26640	22831	11134	15506	13320	13320	17681	8959
Num of HHs	3467	3467	3180	2255	3231	2916	2259	2939	2447

Notes: Table presents estimates of the nonparametric lower bounds on $E[T(P)]$ and the average mean residual risk function, $E[m(P)]$. Column (1) reports the baseline specification. Columns (2) uses only demographic controls; Column (3) uses demographic, job characteristics, and health characteristics. Columns (4)-(9) report results for the baseline specification on various subsamples including below and above age 55 (Columns 4 and 5), above and below-median wage earners (Columns 6 and 7) and above and below 5 years of job tenure. The first row presents estimates of the lower bounds of $E[T(P)]$, which is computed as $1+E[m_Z(P_Z)]/\Pr\{U=1\}$. The value of $E[m_Z(P_Z)]$ is reported in the second row. This is computed using the distribution of predicted values (illustrated in Figure II, Panel A). I construct the average predicted value above a given threshold within an age-by-gender aggregation window; Appendix Table I reports the robustness to alternative aggregation windows. The third row reports the p-value from the test that the coefficients in the probit specification for $\Pr\{U|X,Z\}$ are all equal to zero, clustering the standard errors at the household level. All standard errors for $E[T_Z(P_Z)]$ and $E[m_Z(P_Z)]$ are constructed using 500 bootstrap resamples at the household level.

TABLE III
Minimum Pooled Price Ratio

Specification	Alternative Controls			Sub-Samples					
	Baseline (1)	Demo (2)	Health (3)	Age <= 55 (4)	Age > 55 (5)	Below Median Wage (6)	Above Median Wage (7)	Tenure > 5 yrs (8)	Tenure <= 5 yrs (9)
Inf T(p) - 1	3.360	5.301	3.228	3.325	3.442	4.217	3.223	4.736	3.739
s.e.	(0.203)	(0.655)	(0.268)	(0.306)	(0.279)	(0.417)	(0.268)	(0.392)	(0.336)
Controls									
Demographics	X	X	X	X	X	X	X	X	X
Job Characteristics	X		X	X	X	X	X	X	X
Health Characteristics			X						
Num of Obs.	26,640	26,640	22,831	11,134	15,506	13,320	13,320	17,850	8,790
Num of HHs	3,467	3,467	3,180	2,255	3,231	2,916	2,259	2,952	2,437

Notes: This table presents estimates of the minimum pooled price ratio, $\text{inf T}(p)$. 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

Specification:	Full Sample (1)	Employed in t-1 (2)	Controls for Needs (3)	Individual Fixed Effects (4)	Over 40 Sample (5)	With Outliers (6)	Exclude Food Stamps (7)	p10 (8)	p90 (9)
<i>Panel 1: Reduced Form Impact on $\log(c_{t-1})-\log(c_t)$</i>									
Unemp	-0.0633*** (0.00553)	-0.0761*** (0.00849)	-0.0734*** (0.00886)	-0.0701*** (0.0116)	-0.0599*** (0.0149)	-0.0951*** (0.0120)	-0.164*** (0.0158)	-0.212*** (0.0231)	0.0315*** (0.0133)
s.e.									
<i>Specification Details</i>									
Sample Employed in t-1		X	X	X	X	X	X	X	X
Controls for change in log needs			X	X	X				
Individual Fixed Effects				X					
Mean Dep Var	0.047	0.048	0.049	0.049	0.030	0.055	0.057	0.048	0.048
Num of Obs.	88705	81326	67904	67904	30481	84325	82948	81326	81326
Num of HHs	11964	11290	10469	10469	5529	11441	11230		
<i>Panel 2: First Stage Impact on P</i>									
Δ First Stage	0.803*** (0.012)	0.803*** (0.012)	0.803*** (0.012)	0.803*** (0.012)	0.803*** (0.012)	0.803*** (0.012)	0.803*** (0.012)	0.803*** (0.012)	0.803*** (0.012)
s.e.									
<i>Panel 3: Implied Causal Effect on Consumption</i>									
IV Impact of U on $\log(c_t)$	-0.079*** (0.007)	-0.095*** (0.011)	-0.091*** (0.011)	-0.087*** (0.014)	-0.075*** (0.019)	-0.118*** (0.015)	-0.205*** (0.020)	-0.264*** (0.029)	0.039*** (0.017)
s.e.									
Markup WTP for UI ($\sigma = 2$)	15.8%	18.9%	18.3%	17.4%	14.9%	23.7%	40.9%	52.8%	-7.8%

Notes: This Table presents 2-sample IV estimates of the causal impact of unemployment on consumption, and the implied willingness to pay for UI. Panel 1 reports the coefficients from a regression of the change in log food consumption between years t-1 and t on an indicator of unemployment in year t. The sample includes all household heads in the PSID. Column (1) controls for a cubic in age and year dummies. Column (2) restricts the sample to those who are not unemployed in year t-1. Column (3) adds controls for the change in log expenditure needs ("need_p") between t-1 and t and the change in total household size between t-1 and t. Column (4) adds individual fixed effects to the specification in Column (3). Column (5) restricts the sample to those 40 and over for the specification in Column (3). Following Gruber (1997), Columns (1)-(5) and (8)-(9) drop observations with more than a 3-fold change in consumption and add expenditures from food stamps to food spending in and out of the house; Column (6) includes these outliers following the specification for those who are not unemployed in year t-1. Column (7) uses food expenditures excluding food stamps. Column (8) presents the results from a quantile regression at the 10th quantile for the specification in Column (2). Column (9) 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. The second row presents the The Private WTP multiplies this by a coefficient of relative risk aversion of 2. Standard errors for the consumption drop equivalent are approximated as the reduced form standard errors scaled by the coefficient on U in the first stage. All standard errors in Columns (1)-(7) are clustered at the household level. The quantile regressions in Columns (8)-(9) present robust standard errors. Panel 2 presents the estimated amount of information revealed between the previous year and the subsequent realization of unemployment. Using the HRS sample, the estimates are constructed using a regression of the subjective probability elicitation, Z_t , on an indicator for subsequent unemployment in the next 12 months, U_t . 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
Spousal Labor Supply Relationship to Potential Job Loss

Specification:	Entry									Spouse Unemployment
	Baseline with Z=0 Intercept	No 1 {Z=0} Control	Sample without Future Job Loss	Full Time Work	2yr Lagged Entry ("Placebo")	Household Fixed Effects	Individual Fixed Effects	Exit		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	
<i>Panel 1: Estimation of dL/dZ</i>										
Elicitation (Z)	0.0273** (0.0112)	0.0282*** (0.00868)	0.0270** (0.0116)	0.0286** (0.0128)	0.00792 (0.0102)	0.0267* (0.0146)	0.0312 (0.0230)	0.0170 (0.0116)	0.0250*** (0.00964)	
s.e.										
Elicitation of 0 (1 {Z=0})	-0.000605 (0.00465)		-0.000492 (0.00472)	0.000635 (0.00554)	0.00237 (0.00486)	0.000246 (0.00598)	0.00191 (0.0102)			
<i>Panel 2: Welfare Calculation</i>										
Total Var / Signal Var (var(Z X)/var(P X))	11.00 (1.41)	11.00 (1.40)	11.00 (1.37)	11.00 (1.38)	18.17 (3.90)	11.00 (1.32)	11.00 (1.32)			
W ^{welfare} ($\epsilon^{semi} = 0.5$)	0.6** (0.26)	0.62*** (0.21)	0.59** (0.26)	0.63** (0.30)	0.29 (0.41)	0.59** (0.29)	0.69* (0.39)			
bootstrap s.e.										
Mean Dep Var	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.09	0.03	
Num of Obs.	11049	11049	10726	11049	11049	11049	11049	11049	9079	
Num of HHs	2214	2214	2194	2214	2214	2214	2214	2214	1359	

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

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

TABLE VI
Ex-Ante Drop in Food Expenditure Prior to Unemployment and Implied (Ex-Ante) Willingness to Pay for UI

<i>Specification:</i>	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Full Sample	Employed in t-2 and t-1	Controls for Needs	Individual Fixed Effects	Over 40 Sample	With Outliers	Household Income Controls	Household Head Income Controls
<i>Panel 1: Impact of Unemployment on $\log(c_{t-2})-\log(c_{t-1})$</i>								
Unemp	-0.0336*** (0.00570)	-0.0250*** (0.00942)	-0.0249** (0.00994)	-0.0231* (0.0130)	-0.0287* (0.0151)	-0.0231* (0.0121)	-0.0250*** (0.00935)	-0.0248*** (0.00950)
s.e.								
<i>Specification Details</i>								
Sample Employed in t-2 and t-1		X	X	X	X	X	X	X
Controls for change in log needs (t-2 vs t-1)			X	X	X			
Individual Fixed Effects				X				
Change in log HH inc (t-2 vs t-1) (3rd order poly)							X	
Change in log HH head inc (t-2 vs t-1) (3rd order poly)								X
Mean Dep Var	0.049	0.053	0.054	0.054	0.036	0.060	0.053	0.053
Num of Obs.	80984	70503	58987	58987	27264	72758	70415	69076
Num of HHs	11055	10042	8869	8869	4772	10156	10033	9929
<i>Panel 2: Split-Sample IV Welfare Calculation</i>								
Δ ^{First Stage}	0.103 (0.016)	0.103 (0.016)	0.103 (0.016)	0.103 (0.016)	0.103 (0.016)	0.103 (0.016)	0.103 (0.016)	0.103 (0.016)
bootstrap s.e.								
$d[\log(c_{\text{pnc}}(p))]/dp$ (2-sample 2SLS)	0.33*** (0.06)	0.24*** (0.09)	0.24*** (0.10)	0.22* (0.13)	0.28* (0.15)	0.22* (0.12)	0.24*** (0.09)	0.24*** (0.09)
s.e.								
$W^{\text{ex-ante}} (\sigma = 2)$	0.65*** (0.11)	0.48*** (0.18)	0.48*** (0.19)	0.45* (0.25)	0.56* (0.29)	0.45* (0.23)	0.48*** (0.18)	0.48*** (0.18)
s.e.								

Notes: This Table presents the split-sample IV estimates of the impact of p on log consumption. The sample includes all household heads Panel 1 reports the coefficients from a regression of the change in log food consumption between years t-2 and t-1 on an indicator of unemployment. Column (1) controls for a cubic in age and year dummies. Column (2) restricts the sample to those who are not unemployed in either t-2 or t-1. Column (3) adds controls for the change in log expenditure needs ("need_std_p") between t-2 and t-1 and the change in total household size between t-2 and t-1. Column (4) adds individual fixed effects to the specification in Column (3). Column (5) restricts the sample to those 40 and over for the specification in Column (3). Following Gruber (1997), Columns (1)-(5) and (7)-(8) drop observations with more than a 3-fold change in consumption; Column (6) includes these outliers following the specification for those who are not unemployed in both t-1 and t-2. Column (7) adds controls to the specification in Column (2) for a third degree polynomial in the household's change in log income between years t-2 and t-1. Column (8) adds controls to the specification in Column (2) for a third degree polynomial in the household head's change in log income between years t-2 and t-1. Panel 2 reports the impact of unemployment on the elicitation. The first row reports the difference in the coefficient from a regression of the elicitation, Z, on subsequent unemployment in the next year, U, and the coefficient from a regression of Z on an indicator for unemployment in Column (2) for 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 unemployment to arrive at the estimate of $d\log(c)/dp$. 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 VII
Social Willingness to Pay for Unemployment Insurance

<i>Ex-ante Method:</i>	Ex-Ante Consumption Drop			Ex-Ante Spousal Labor Supply				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Social WTP, W^{social}	0.248	0.124	0.361	0.271	0.389	0.231	0.194	0.347
Insurance against p , $W^{ex-ante}$	0.485	0.242	0.672	0.602	1.204	0.401	0.602	0.602
Weight, $E[P U=1] - E[P U=0]$	0.197	0.197	0.197	0.197	0.197	0.197	0.197	0.197
Insurance against U (given p), $W^{ex-post}$	0.189	0.095	0.284	0.189	0.189	0.189	0.095	0.284
Weight, $1 - (E[P U=1] - E[P U=0])$	0.803	0.803	0.803	0.803	0.803	0.803	0.803	0.803
<i>Specification Details</i>								
Coeff. Of Relative Risk Aversion, σ	2	1	3	2	2	2	1	3
Spousal Labor Supply Semi-Elasticity, ϵ^{semi}	N/A	N/A	N/A	0.50	0.25	0.75	0.50	0.50

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 (σ and ϵ^{semi}) and the method used to calculate the ex-ante insurance value (consumption response versus spousal labor supply response). Columns (1)-(3) use the ex-ante consumption drop in Column (2), Table VI to value insurance under different assumptions for risk aversion. Columns (4)-(7) use the spousal labor supply response in Table V, Column (1), to measure the ex-ante insurance value, and provide a range of estimates for various labor supply semi-elasticities and coefficients of relative risk aversion (which continues to affect the value of insurance against U given p).

APPENDIX TABLE I
Alternative Lower Bound Specifications

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

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

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

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

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

APPENDIX TABLE III
Summary Statistics (PSID Sample)

	mean	std dev
<i>Variable</i>		
Age	39.794	10.27
Male	0.808	0.39
Unemployment	0.059	0.24
Year	1985	7.62
Log Consumption	8.199	0.65
Log Expenditure Needs	8.124	0.32
 <i>Consumption growth ($\log(c_{t-2})-\log(c_{t-1})$)</i>	 0.049	 0.360
 <i>Sample Size</i>		
Number of Observations	80,984	
Number of Households	11,055	

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
Ex-Post Consumption Relationship to Ex-Ante Knowledge About Job Loss

<i>Specification:</i>	Baseline	HH Cons	Sample Z > 0	Sample U = 0	Non-Durable Consumption	No Controls	No 1 {Z=0} Control
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Elicitation (Z) s.e.	-0.160** (0.0781)	-0.110* (0.0596)	-0.171** (0.0777)	-0.162** (0.0783)	-0.162** (0.0789)	-0.345*** (0.0798)	-0.0401 (0.0659)
Elicitation * Unemp (Z*U) s.e.	-0.137 (0.268)	-0.421** (0.207)	-0.0771 (0.268)		-0.257 (0.303)	-0.0000475 (0.296)	-0.460** (0.218)
Elicitation of 0 (1 {Z=0}) s.e.	-0.0893*** (0.0334)	-0.0587** (0.0279)		-0.0904*** (0.0334)	-0.120*** (0.0356)	-0.160*** (0.0365)	
Elicitation of 0 * Unemp (1 {Z=0} * U) s.e.	0.338 (0.222)	0.161 (0.180)			0.307 (0.220)	0.191 (0.239)	
Unemp (U) s.e.	-0.0845 (0.165)	0.0862 (0.128)	-0.120 (0.164)		-0.0936 (0.164)	-0.181 (0.187)	0.118 (0.120)

Mean Dep Var	9.86	10.58	9.89	9.87	9.18	9.86	9.86
Num of Obs.	2,798	2,798	1,503	2,696	2,798	2,798	2,798
Num of HHs	862	862	579	843	862	862	862

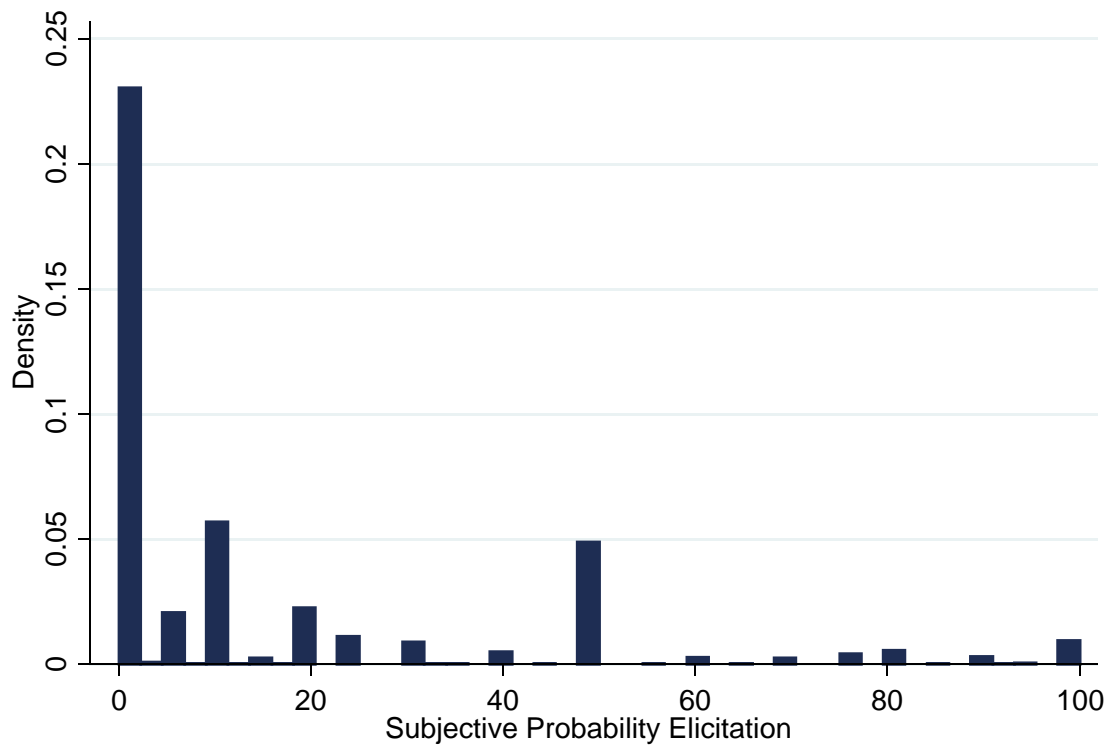
Notes: This table presents estimates from a regression of log consumption expenditure on subjective elicitation of becoming unemployed and indicators of the event of actually becoming unemployed in the subsequent 12 months. Consumption expenditure is measured 12 months after the subjective probability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

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

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

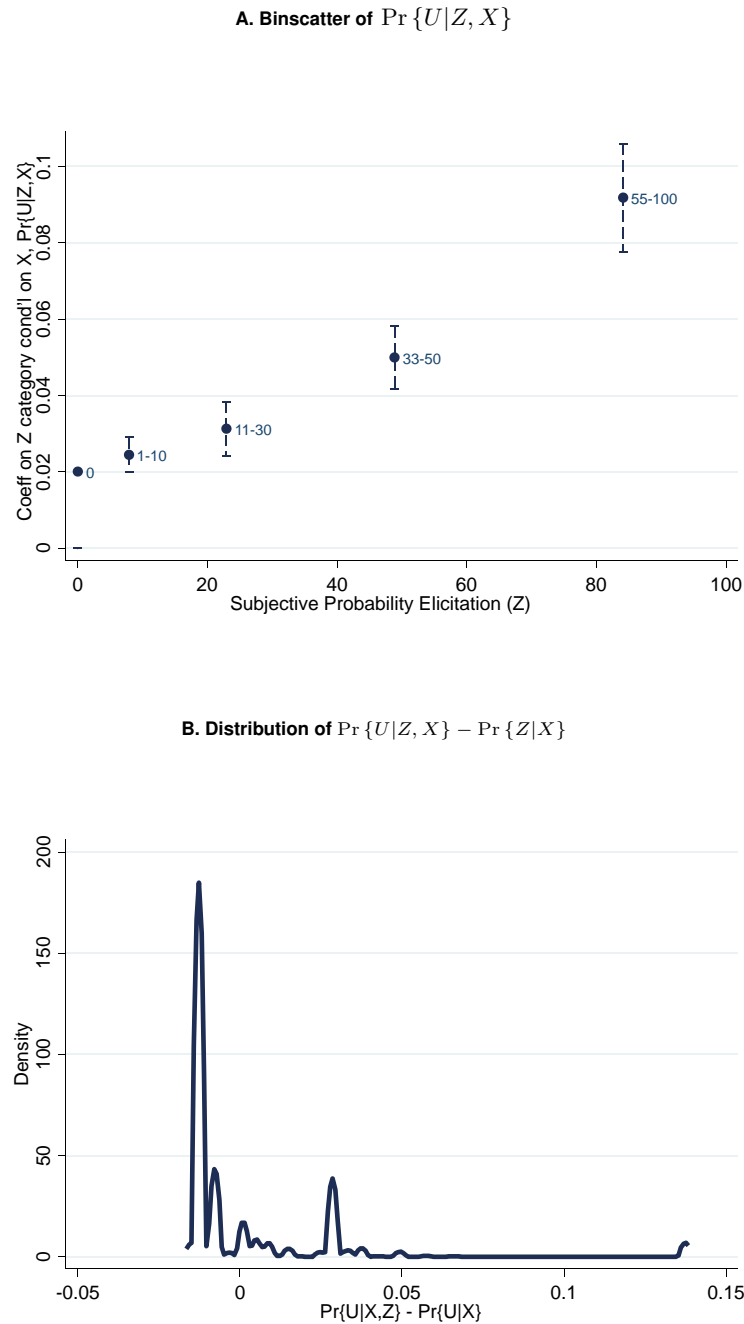
Note: This table presents estimates from two separate regressions of the elicitation on unemployment in the subsequent 12 months (U) and the elicitation, Z, on unemployment in the 12-24 months after the elicitation. The standard error for the difference is computed using 500 bootstrap repetitions resampling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

FIGURE I: Histogram of Subjective Probability Elicitations



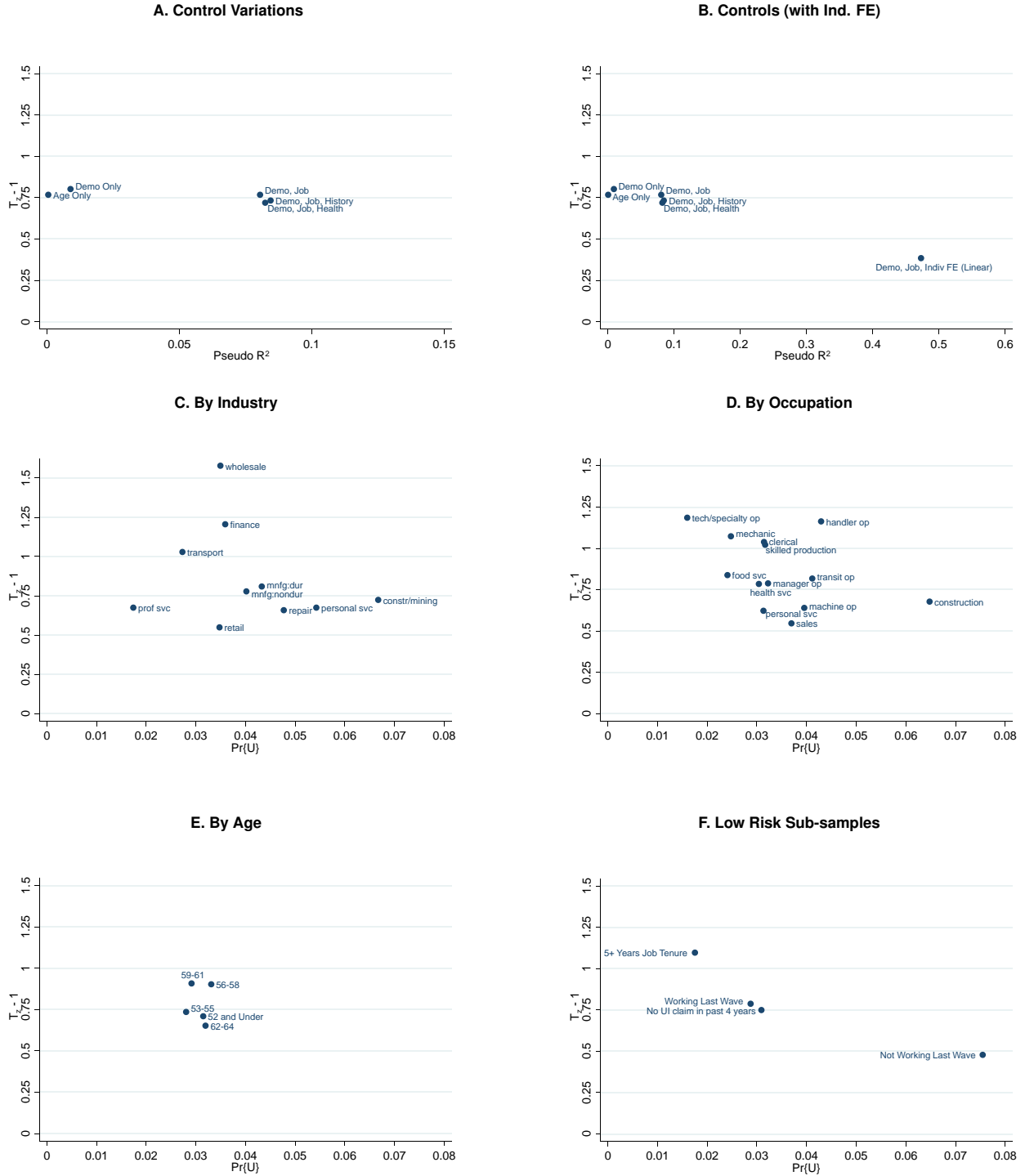
Notes: This figure presents a histogram of responses to the question “What is the percent chance (0-100) that you will lose your job in the next 12 months?”. The figure reports the histogram of responses for the baseline sample outlined in Panel 1 of Table I. As noted in previous literature, responses tend to concentrate on focal point values, especially $Z = 0$.

FIGURE II: Predictive Content of Subjective Probability Elicitations



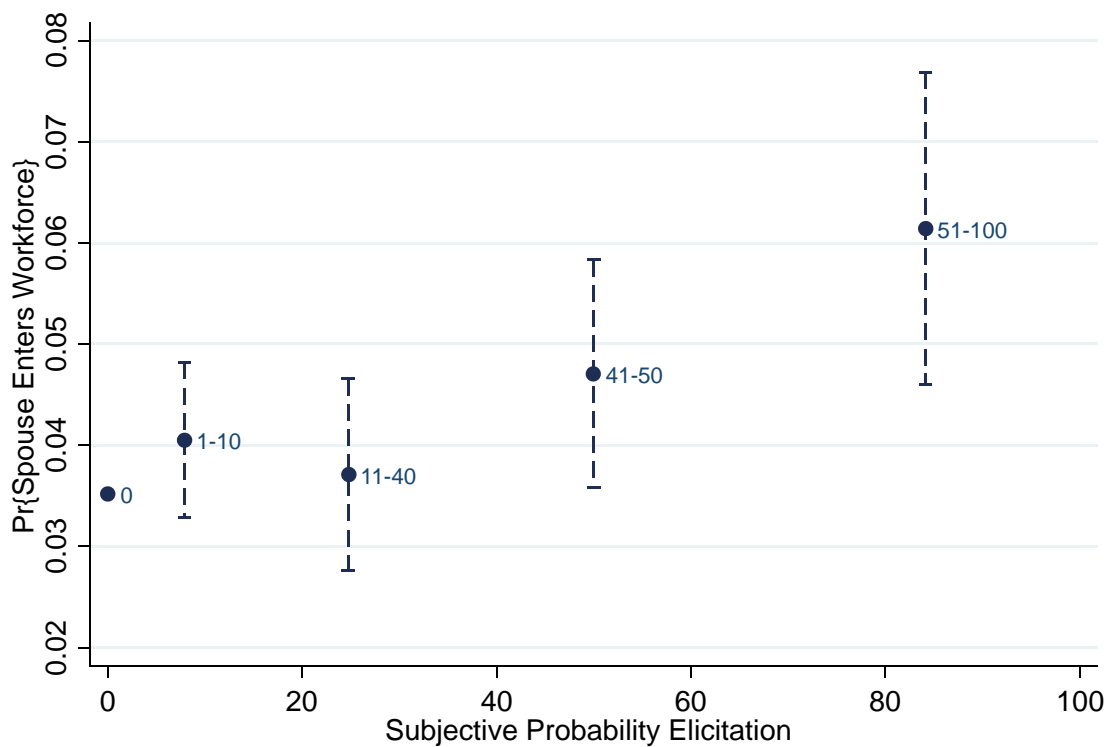
Notes: These figures present the predictive content in the subjective probability elicitation. Panel A reports the mean unemployment rate in each elicitation category controlling for demographic and job characteristics. To construct this figure, I first regress the unemployment indicator on the demographic and job characteristics and take the residuals. I then construct the mean of these residuals in each of the elicitation categories and add back the mean unemployment rate. To obtain the 5 / 95% confidence intervals, I run a regression of unemployment on each of these categories with zero as the omitted category, clustering the standard errors by household. Panel B reports the kernel density of the distribution of predicted values from a regression of both observables and the elicitation on U , $\Pr\{U|X, Z\}$, minus the predicted values from a regression of U on observables, X , $\Pr\{U|X\}$. Under the Assumptions outlined in the text, the true distribution of P given X is a mean-preserving spread of this distribution of predicted values.

FIGURE III: Lower Bounds for $E[T(P)]$



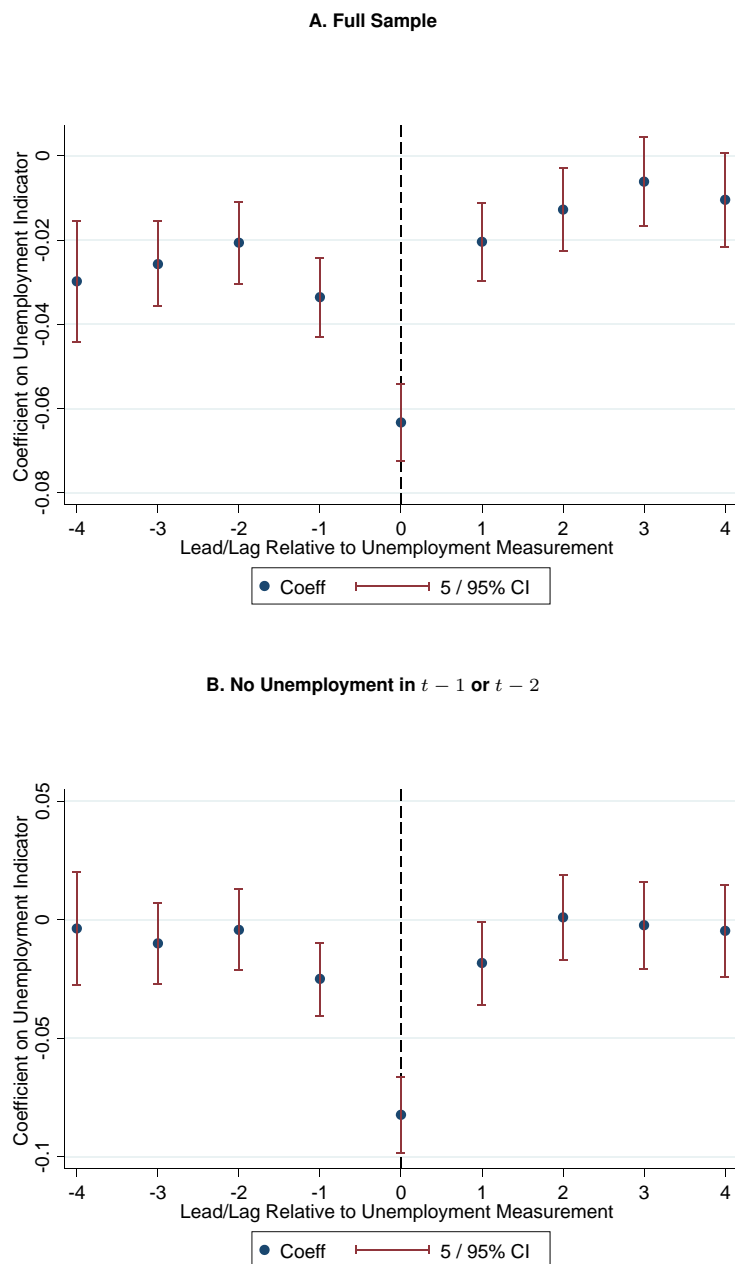
Notes: These figures present estimates of the lower bounds on the average pooled price ratio, $E[T_Z(P_Z)]$, using a range of sub-samples and controls. Panel A reports estimates of $E[T_Z(P_Z)]$ for a range of control variables. Panel B adds a specification with individual fixed effects to Panel A and relies on a linear specification as opposed to a probit (see Appendix Table I, Column (2) for the baseline estimation using the linear model). The horizontal axis presents the Pseudo- R^2 of the specification for $\Pr\{U|X, Z\}$. Panel C constructs separate estimates by industry classification. Panel D constructs estimates by occupation. Panel E constructs separate estimates for each wave of the survey. Panel F restricts the sample to varying sub-samples, analyzing the relationship between $E[T_Z(P_Z)]$ and restrictions to lower-risk subsamples. The horizontal axis in Panels C-F report the mean unemployment probability, $\Pr\{U\}$, for each sub-sample.

FIGURE IV: Relationship between Potential Job Loss and Spousal Labor Supply



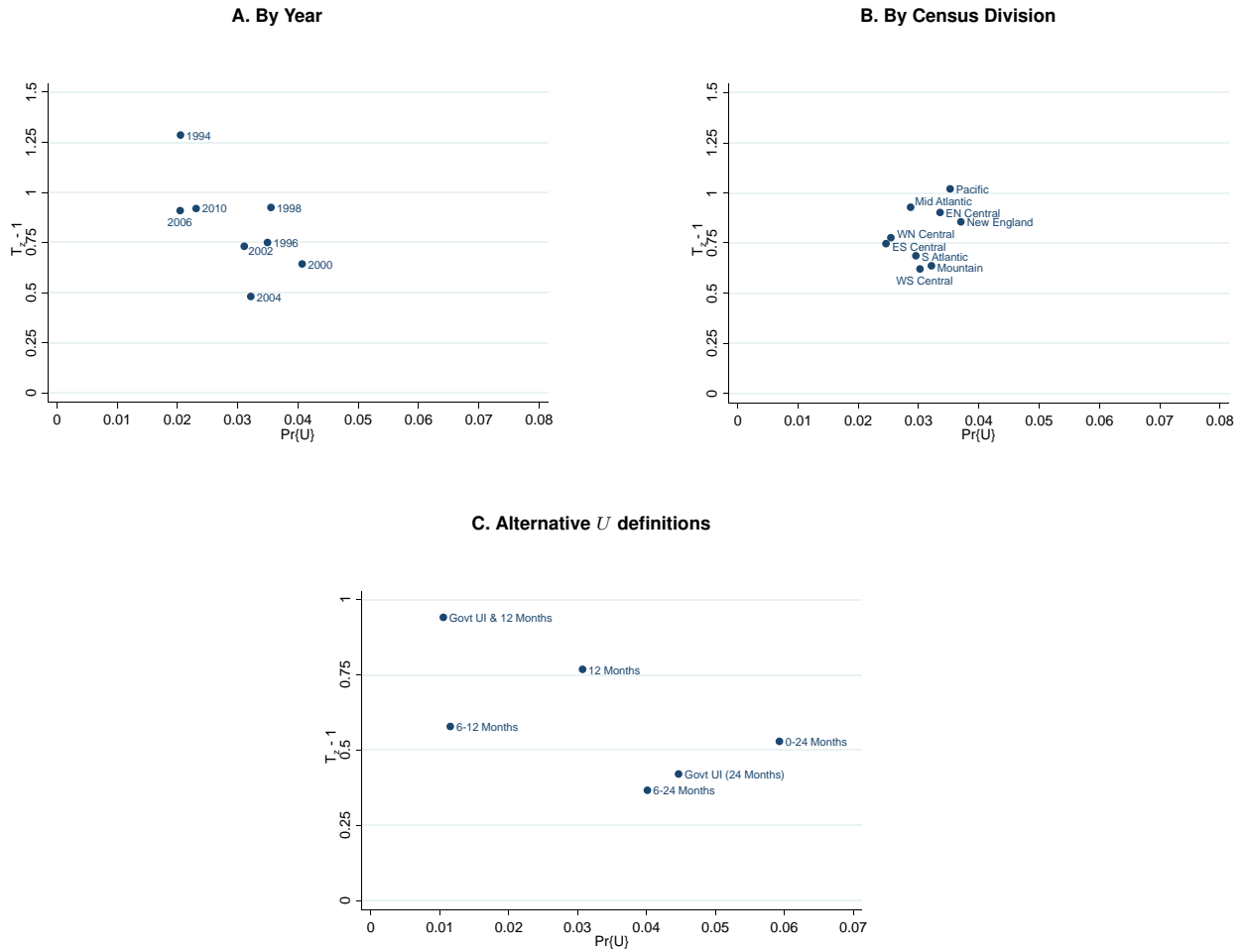
Notes: The figure present coefficients from a regression of an indicator for a spouse entering the labor force – defined as an indicator for not working in the previous wave and working in the current wave – on category indicators for the subjective probability elicitation, Z , controlling for realized unemployment status, U , and several observable characteristics: age, age squared, gender, year dummies, census division, log wage, and an indicator for being married.

FIGURE V: Impact of Unemployment on Consumption Growth



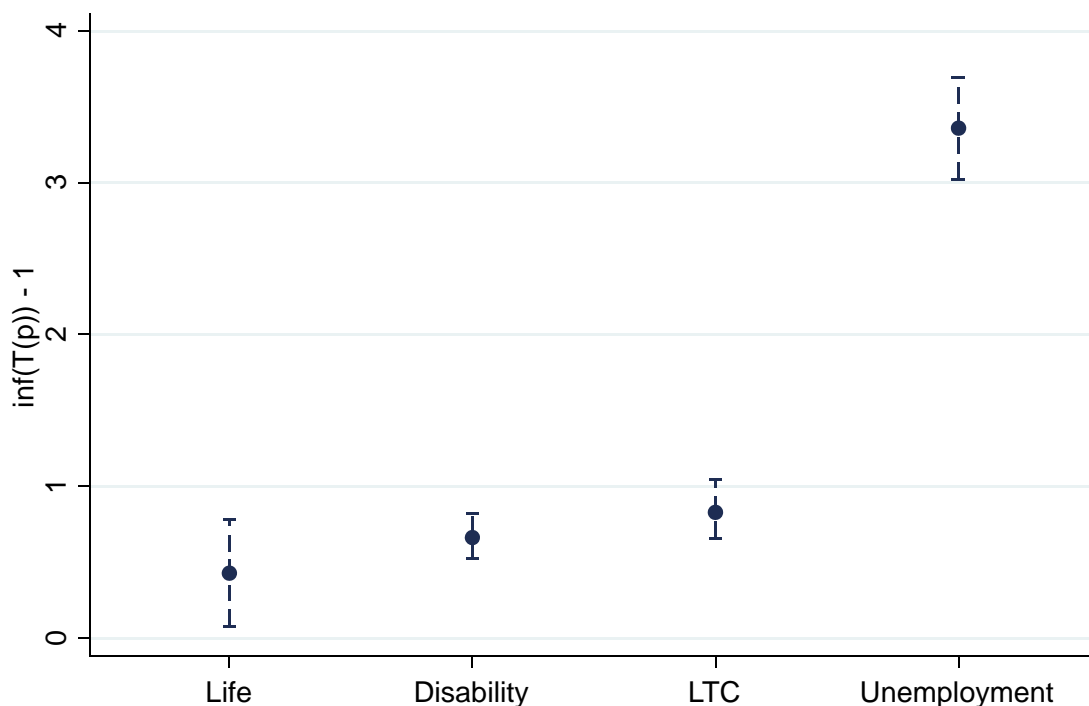
Notes: These figures present coefficients from separate regressions of leads and lags of the log change in food expenditure on an indicator of unemployment, along with controls for year indicators and a cubic in age. Sample is restricted to household heads. Food expenditure is the sum of food in the home, food outside the home, and food stamps. Following Gruber (1997) and Chetty et al. (2005), I define food stamps by taking the monthly measure and multiplying by 12 for the years where the monthly food stamp measure is available. The horizontal axis presents the years of the lead/lag for the consumption expenditure growth measurement (i.e. 0 corresponds to consumption growth in the year of the unemployment measurement relative to the year prior to the unemployment measurement). Panel A presents the results for the full sample. Panel B restricts the sample to household heads who are not unemployed in $t - 1$ or $t - 2$.

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



Notes: This figure presents additional estimates of the lower bound on the average pooled price ratio, $E[T_Z(P_Z)]$. 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 $E[T_Z(P_Z)]$ in a hypothetical underwriting scenario whereby insurers would impose 6 month waiting periods. I also include specifications that interact these indicators with indicators that the individual had positive government UI claims, which effectively restricts to the subset of unemployment spells where the individual takes up government UI benefits.

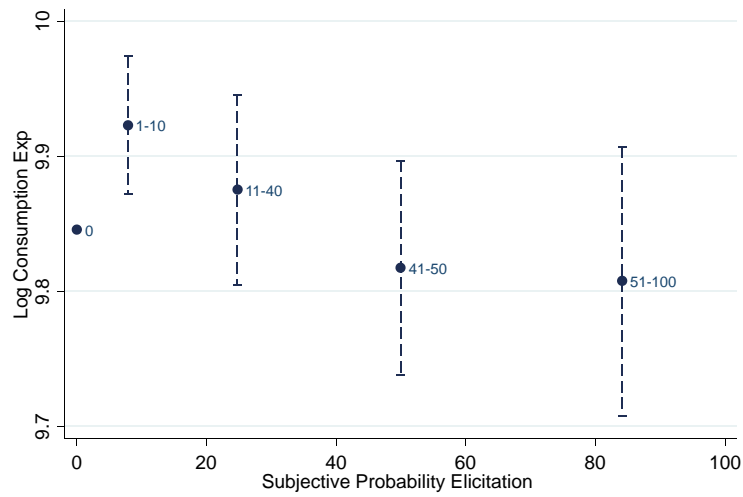
ONLINE APPENDIX FIGURE II: Comparison to Other Non-Existing Insurance Markets



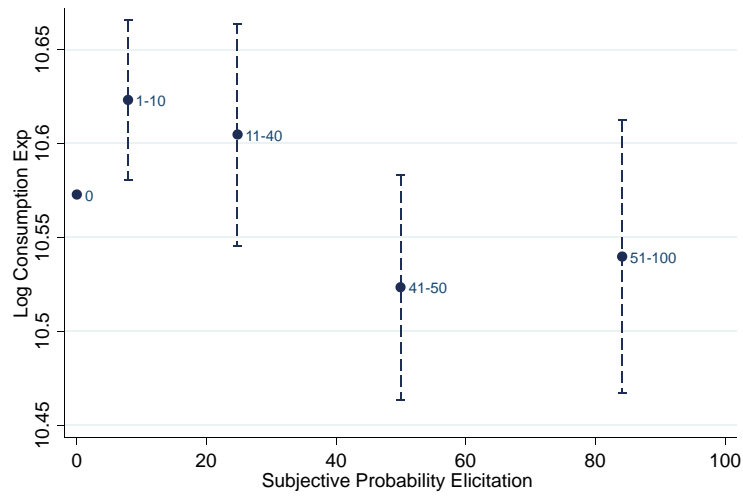
Notes: Hendren (2013) argues private information prevents people with pre-existing conditions from purchasing insurance in LTC, Life, and Disability insurance markets. This figure compares the estimates of $\inf T(p) - 1$ for the baseline specification in the unemployment context to the estimates in Hendren (2013) for the sample of individuals who are unable to purchase insurance due to a pre-existing condition. Figure reports the confidence interval and the 5 / 95% confidence interval for each estimate in each sample.

ONLINE APPENDIX FIGURE III: Relationship between Potential Job Loss and Consumption

A. Household Consumption Per Capita

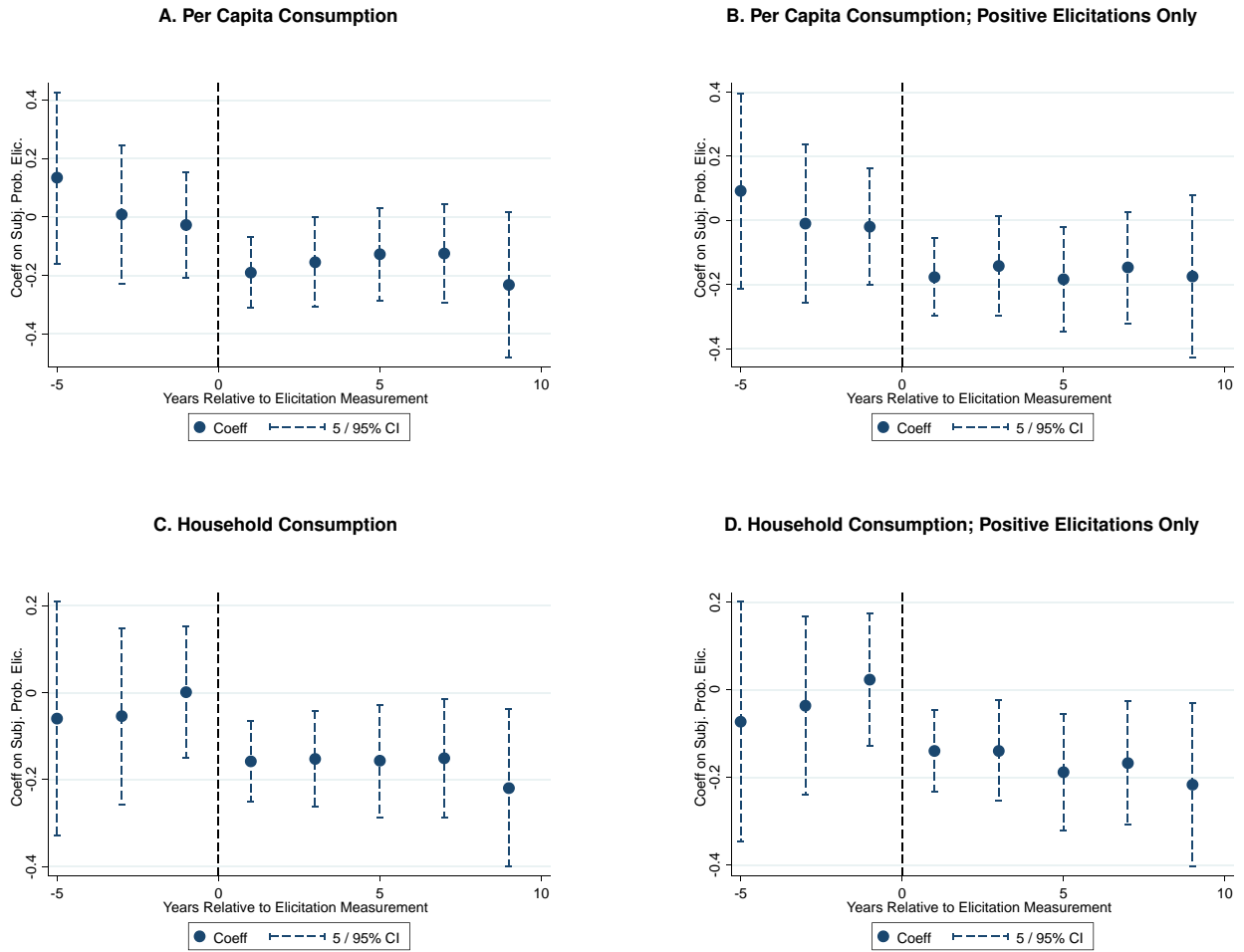


B. Household Consumption



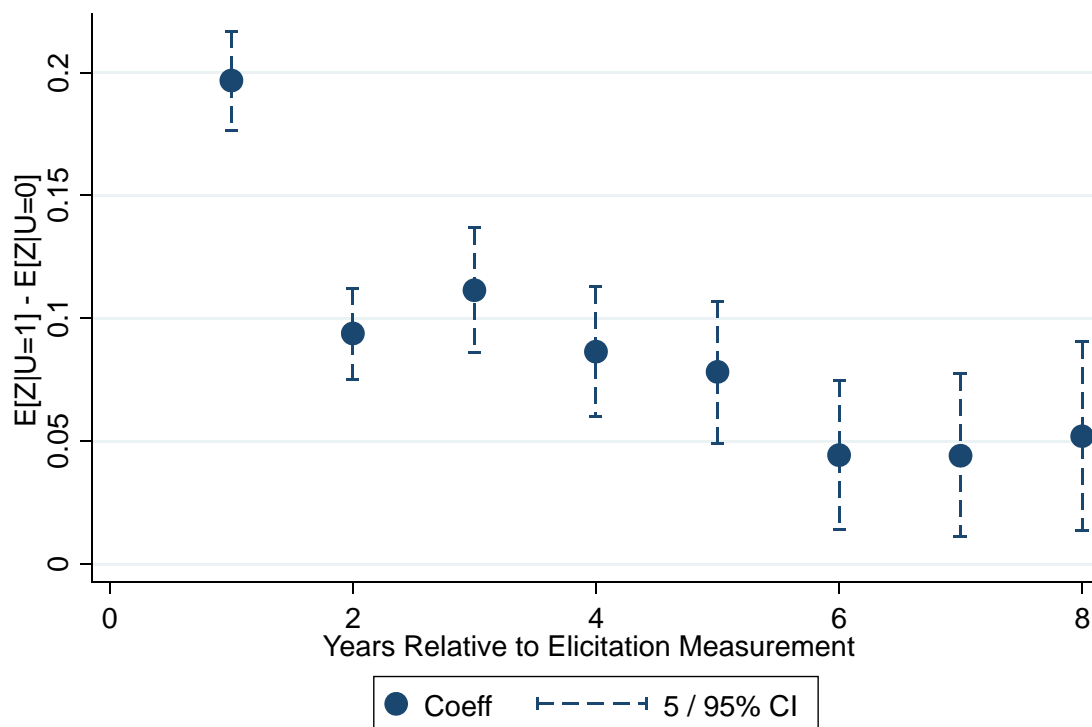
Notes: These figures present coefficients from a regression of log household consumption per capita (Panel A) and log total household consumption (Panel B) on category indicators for the subjective probability elicitation, Z , controlling for realized unemployment status, U , and several observable characteristics: age, age squared, gender, year dummies, census division, log wage, and an indicator for being married.

ONLINE APPENDIX FIGURE IV: Relationship between Potential Job Loss and Consumption Leads and Lags



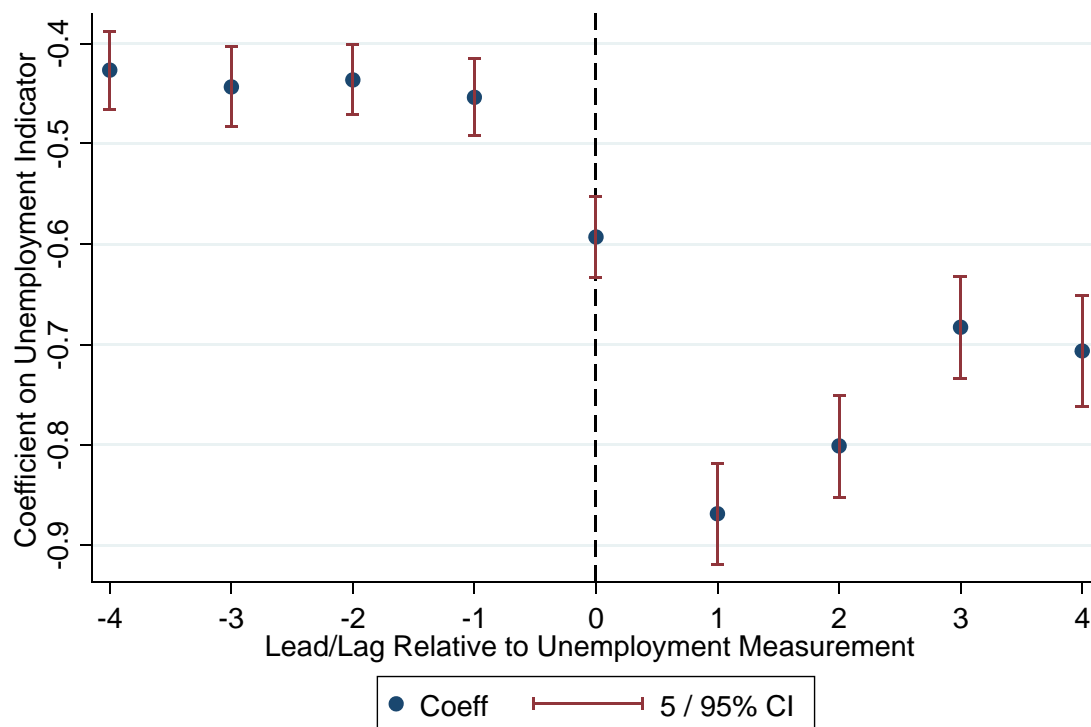
Notes: These figures present coefficients from a regression of leads and lags of log per capita consumption (Panels A and B) and log household consumption (Panels C and D) on the subjective probability elicitations, controlling for an indicator for realized unemployment, an indicator for a subjective probability elicitation of $Z = 0$, and several observable characteristics: age, age squared, gender, year dummies, census division, log wage, and an indicator for being married. Panels A and C include all observations; Panels B and D restrict the sample to those with positive elicitations, $Z > 0$. The vertical dotted line corresponds to the time of the subjective probability elicitation. The horizontal axis corresponds to the time of the consumption measurement (which includes a 12 month look-back window).

ONLINE APPENDIX FIGURE V: “First Stage” Impact of Unemployment on Beliefs



Notes: This figure presents the estimated coefficients of a regression of the elicitation (elicited in year t) on unemployment indicators in year $t + j$ for $j = 1, \dots, 8$. 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.

ONLINE APPENDIX FIGURE VI: Household Income Pattern Around Unemployment



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