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Richard G. Anderson
And
Charles S. Gascon

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FEDERAL RESERVE BANK OF ST. LOUIS
Research Division
P.O. Box 442
St. Louis, MO 63166

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Richard G. Anderson
randerson@stls.frb.org

Charles S. Gascon
charles.s.gascon@stls.frb.org

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Abstract

The fear of offshoring, particularly in services since 2000, has raised workers economic insecurity and heightened concerns over future economic globalization. Many have argued that globalization has exacerbated labor market turbulence increasing the demand for social insurance programs. The authors present a simple theoretical model establishing a connection between the threat of offshoring, economic insecurity, and the demand for social insurance. Data from the 1972-2006 General Social Survey to provides supporting empirical evidence.

Keywords: economic insecurity, offshoring, social insurance, trade adjustment assistance

JEL classification: F16; J31; J65

1 Introduction

Trends in workers' perceived economic insecurity have moved closely with the unemployment rate over the past three decades (see figures 1 and 2). However, since the mid 1990s the average level of economic insecurity has failed to trend downward with the unemployment rate. This apparent rise in insecurity has focused attention on future economic globalization. Rodrik (1997), Scheve and Slaughter (2004), and Traca (2005), among others, find that higher levels of economic insecurity result from greater wage and employment volatility, which is a product of trade-induced increases in labor-demand elasticities. Moreover, Rodrik (1998) claims there is a positive relationship between increased economic integration and the size of the welfare state.

Rodrik (1998) argues that the government can play a risk-reducing role, as workers exposed to higher levels of international trade are exposed to more labor market risk. This "risk" is essentially the higher volatility in wages and employment from a more elastic demand for labor. Traca (2005) finds evidence to support this hypothesis. Slaughter (2001), however, finds "mixed [empirical] support" for the hypothesis that trade has contributed to increased labor demand elasticities. Furthermore, Iversen and Cusack (2000) find that changing welfare preferences can be explained by *internal* labor market transformations and not globalization. Panagariya (1999) directly refutes Rodrik's hypothesis.[1]

Cusack, Iversen, and Rehm (2006) (henceforth CIR) focus on how labor market risk is related to preferences for redistribution. CIR use the popular International Social Survey Programme (ISSP) and industry-level data to establish; which *objective* measures of insecurity (labor market indicators) determine preferences for redistribution; and whether objective measures are good predictors of subjective economic insecurity.[2] CIR find that in both cases labor market indicators are statistically significant predictors of welfare policy preferences and perceived insecurity. The purpose of the second regression is, as CIR note, because "it is not obvious that people have a good idea about their actual exposure to risk" and, from a political economy standpoint, perceptions of risk should be more important in determining policy preferences. If voters' perceptions are overly pessimistic about the condition of the economy, they could demand government action, even if it is unnecessary.[3]

On the other hand, Mughan (2007) finds that "no form of [subjective] job insecurity has any impact on the support for enhanced social welfare provisions." Mughan's findings indicate it may not be safe to conclude that objective measures of insecurity are good estimates of perceived insecurity or that workers who *believe* they are exposed to more risk demand more social insurance. Obviously these conflicting results are data driven: CIR use 1970-2004 cross-national data, while Mughan uses two separate surveys, a 1995 U.S. survey and 1998 Austrailian survey. Fomenting the problem are significant differences in the questions used to estimate welfare policy preferences, which we will discuss later. Mughan concludes "despite these findings...the thesis [that insecurity determines welfare preferences] should not be rejected." However, recent work by Campbell, Carruth, Dickerson, and Green (2007) indicate that Mughan's results may hold water.[4]

In light of the literature reviewed above, we use data from the 1972-2006 General Social Survey (GSS) that corresponds nicely with the survey data used by CIR and Mughan. With a few exceptions (Aaronson and Sullivan, 1998; Schmidt, 1999), the GSS has not been fully utilized to study the issue of economic insecurity. We find that increased international exposure (specifically offshoring) has increased workers *perceived* economic insecurity. While this result is not

[1] To summarize, Panagariya (1999) uses two popular trade models (the 2x2 H-O model and the specific-factors model) to demonstrate that the labor-demand curve *many not* need to be more elastic in an open economy than in a closed one.

[2] CIR note that the ISSP does not contain a sample of respondents who are asked about both their own job security and about welfare policy preferences. Consequently, they run two seperate regressions and different samples of the data.

[3] One possible reason to expect this result is that the media tends to portray the economy as being worse than the data indicate. For example see Blendon et al., (1997).

[4] Campbell et al. find that expectations data are additionally informative and contain useful private information for predicting future unemployment. This suggests that using an objective measure may produce misleading results.

surprising, this paper is the first, to our knowledge to reach this conclusion using U.S. data. Secondly, we find that workers who express higher levels of insecurity tend to demand that the government should; play a larger role in redistributing income from the rich to the poor; and spend more money on healthcare, welfare, and social security programs. Conversely, we find no evidence that insecure workers want the government to spend more money on education. The next sections set forth a simple theoretical model connecting offshoring, labor demand elasticities and the demand for social insurance. Section 3 reviews the GSS data and the construction of our variables. Section 4 outlines our empirical strategy and results. The final section concludes and proposes some areas for future research.

2 Theory

Economic insecurity is most often understood as an individual's perception of the risk of economic misfortune (e.g. Dominitz and Manski, 1997). Economic misfortune can be thought of as individual's inability to purchase goods and services or provide for their families, actions that primarily depend on their income. In reality, the majority of Americans do not earn their primary income from dividend payments or stock options, but rather from wages from labor income. We make the standard assumption that economic insecurity primarily stems from volatility in wages and employment, caused by volatility in the labor market. As a result, the first part of this section uses labor theory in conjunction with trade theory to review the argument that offshoring affects economic insecurity via increases in industries' labor-demand elasticities.[5] The result that follows—workers susceptible to offshoring will express a higher probability of a job loss than workers in safe industries—is used in an expected utility model, in which workers' demand for wage insurance is a function of their expected probability of a costly job loss.

2.1 Offshoring and labor market volatility

The effect of increased globalization may be illustrated with a simple, perfect-competition, industry-level labor demand model (e.g., Hamermesh, 1993). Let an industry's own-price labor demand elasticity, n_j^d, consist of two parts, a *scale effect* (sn_j) and a *substitution effect* ($-1[1-s]\sigma_j$):

$$n_j^d = -1[1-s]\sigma_j - sn_j, \tag{1}$$

where s is labor's share of industry j's total revenue; σ_j is the constant-output elasticity of substitution between labor and all other factors of production; and n_j is the product-demand elasticity for industry j's output market. n_j^d is defined as negative; s, σ_j, and n_j are positive. The scale effect measures the change in the quantity of labor demanded after a wage change caused by a change in output. The substitution effect tells us, for a given level of output, how much firms substitute away from labor and toward other factors of production

[5] The section 2.1 follows closely with the reasoning presented by Slaughter (2001).

when wages rise. Both the scale and substitution effects reduce the quantity of labor demanded when wages rise. For the purpose of this paper, we focus on the processes in which offshoring increases labor-demand elasticities via the substitution effect.[6]

Suppose an industry is vertically integrated with a number of production stages. Trade allows domestic firms to lower production costs by offshoring work to foreign labor and importing intermediate inputs (e.g., Feenstra and Hanson, 1996, 1999). Trade thus increases the number of factors that firms can substitute in response to higher domestic wages, beyond simply domestic non-labor factors. Therefore, movement toward freer trade should increase the elasticity of substitution, σ_j. Firms need not actually offshore jobs to increase σ_j; the potential of offshoring is sufficient (Slaughter, 2001). Differentiating (1) with respect to σ_j shows that, as this substitutability increases, labor demand becomes more elastic (i.e., n_j^d becomes more negative):

$$\frac{\partial n_j^d}{\partial \sigma_j} = -[1-s]. \tag{2}$$

Additionally, as s decreases the pass-through from σ_j to n_j^d strengthens. As a result, we would expect to see higher wages generate larger changes in the quantity of labor demanded for industries with more capital intensive an production.[7] It can be easily shown[8] that higher labor-demand elasticities increase the volatility in wages and employment (e.g., Scheve and Slaughter, 2004). Increased economic insecurity thus reflects workers' response to the greater volatility in employment and wages within their industry (Rodrik, 1997).

2.2 Expected utility model

Assume a workers' demand for social insurance is based on his desire to have the same level of consumption even if an adverse event, such as a costly job loss, befalls him. His expected utility is such that:

$$EU_i = (1-p_i) \times U(W_i - t_i b_i) + p_i \times U(W_i - \delta_i - t_i b_i + b_i)\ , \tag{3}$$

where p_i is the probability worker i will experience costly job loss, W is i's income regardless of whether he experiences a costly job loss,[9] t_i is the tax per

[6] Scheve and Slaughter (2004) note two reasons for focusing on the substitution effect; because it is direct (i.e., it places domestic workers in competition with foreign labor) and because other researchers (primarily Rodrik, 1997) have emphasized in theory its possible role in generating insecurity.

[7] This is where the role of increasing automation affects labor-demand elasticities. Increases in automation will reduce s, increasing the pass-through effect. Replacing workers with computers will exacerbate the impact of trade on the labor-demand elasticity.

[8] Let z denote the marginal product of labor; let w and e denote the percent change in wages and employment ,which are given by $w = \left(\frac{\eta^s}{\eta^s+\eta^d}\right) z$, and $e = \left(\frac{\eta^s\eta^s}{\eta^s+\eta^d}\right) z$; and let z be a random variable so that $\sigma_w^2 = \left(\frac{\eta^s}{\eta^s+\eta^d}\right)^2 Var(z)$ and $\sigma_e^2 = \left(\frac{\eta^s\eta^s}{\eta^s+\eta^d}\right) Var(z)$. For a graphic, see Rodrik (1997, p. 16).

[9] W consists of wage (salary and benefits) as well as non-wage income (wealth). This becomes an important consideration in our empirical model specification, although not necessarily a critical assumption.

dollar that i incurs for the government to provide him with wage insurance, δ_i is total amount of salary (and benefits) lost if i loses his job and cannot find a job with similar pay and benefits, and b_i is the amount the government will pay him if he does experience a costly job loss. Assume the government works on a balanced budget, such that expected profits ($E\pi$) are

$$\begin{aligned} E\pi &= tb - pb = 0 \\ \therefore \quad & t = p \ , \end{aligned} \tag{4}$$

where there are no administrative costs and the taxes received equal the expected benefits paid out. Therefore, if the probability of costly job loss for worker i is 5% then $t = 5$ cents per dollar. Maximizing expected utility, where $U = \sqrt{C}$ so

$$EU_i = (1 - p_i)\sqrt{(W_i - p_i b_i)} + p_i\sqrt{(W_i - \delta_i - p_i b_i + b_i)} \ . \tag{5}$$

Maximizing (5) with respect to b_i gives us the optimal level of social insurance for worker i is

$$\begin{aligned} \frac{\partial}{\partial b_i} &= \frac{-p_i(1-p_i)}{\sqrt{(W_i - b_i p_i)}} + \frac{p_i(1-p_i)}{\sqrt{(W_i - \delta_i - p_i b_i + b_i)}} = 0 \\ \therefore \quad & b_i^* = \delta_i \ . \end{aligned} \tag{6}$$

This is to say worker i is willing to pay taxes at a level where the government assistance exactly offsets his loss of income and benefits if he experiences a costly job loss. It follows that consumption is equalized where

$$W_i - p_i \delta_i \ . \tag{7}$$

The problem of adverse selection occurs if we have two types of workers. One is susceptible to offshoring, with a probability p_t of experiencing a costly job loss. The second group of workers is safe from offshoring and has a probability p_n of costly job loss where $p_n < p_t$. Providers of social insurance know the proportions of the population that fall into each group but are unable to distinguish between the two groups of workers. Therefore the government must charge a tax rate t_n on every worker; however $t_n < t_t$ and the profits earned on the two groups of workers are

$$E\pi_n = t_n b_n - p_n b_n = 0, \text{ and} \tag{8}$$

$$E\pi_j = t_t b_t - p_t b_t < 0 \ . \tag{9}$$

Where the government breaks even on the group of workers safe from offshoring, and since $p_t > p_n$, the government operates at a loss overall and therefore private social insurance would not be offered by the free market.

Using data from the Displaced Worker Survey from Kletzer (2007, Tables 7 and 9), we can estimate the optimal tax rates and the cost of a wage insurance program for workers in tradable and nontradable industries. We calculate the percent of workers who will experience a costly job loss ($\hat{p}$) as follows:

$$\hat{p} = ru + rs(1 - u) \ , \tag{10}$$

where u is the percentage of workers that remain unemployed after job loss, r is the job loss rate, and s is the share of workers that take a loss in earnings after re-employment.

Table 1 shows that workers in tradable industries experience a greater decline in income when faced with job loss compared with those workers in nontradable industries. However, workers in tradable industries have slightly higher annual incomes than their counterparts.[10] From equation (7) we estimate the steady-state levels of consumption and the optimal tax rates. The model predicts that workers in tradable industries would be willing to pay 2.3 percent of their annual income in taxes in return for wage insurance, while workers in nontradable industries are willing to pay only 0.5 percent of their annual income in taxes. These conditions set the total cost of a wage insurance program at $31 billion.

The pitfall of this approach is that the $\hat{p}$ is the current proportion of workers who experienced a costly job loss and not the probability of future job loss, which raises the problem of adverse selection described above; the question noted by CIR, is also raised: Are objective measures good proxies for expectations? We address this issue in the following sections.

3 Data

Our data are from the General Social Survey conducted by the National Opinion Research Center of the University of Chicago. The survey is administered in February and March of each sample year, with the total number of respondents ranging from 1,468 to 2,832. Since 1994, the GSS has been conducted on a biannual basis. Respondents answer questions regarding their demographic information and opinions on a plethora of topics, including two questions about earnings and employment expectations, and a dozen questions about government spending. We use the responses from the two employment questions to measure perceived economic insecurity. So far as we are aware, this is the only large survey dataset for the United States that contains such questions.

3.1 Variables to capture workers' economic insecurity

The first question, which we label *joblose*, asks: "Thinking about the next 12 months, how likely do you think it is that you will lose your job or be laid off—very likely, fairly likely, not too likely, or not at all likely?" The second question, which we label *jobfind*, asks: "About how easy would it be for you to find a job with another employer with approximately the same income and fringe benefits you now have? Would you say very easy, somewhat easy, or not easy at all?"

Figures 1 and 2 plot the percentage of respondents who believe it is likely and very likely they will lose there job (LIL) and believe it would be hard to find a new job over the sample period (HDF). The figures exhibit two notable patterns. First, workers' expectations about losing their job and finding

[10]This result is in stark contrast with other social insurance models,(e.g., Moene and Wallerstein, 2001) that assume 2 groups of workers: a high-income group with zero probability of costly job loss and a low-income group with a high probability of costly job loss.

a new job have moved fairly closely with the unemployment rate. This pattern is consistent with CIR's finding that labor market indicators are good proxies for perceived economic insecurity. Second, during the economic recovery of the 1990s and to a greater extent the recovery in the 2000s, workers were more pessimistic about both job loss and finding a job than they were during the previous periods of relatively low unemployment in within the period of the 1970s and 1980s, this trend is highlighted by the growing divergence with the unemployment rate. This divergence, beginning around 2000 (specifically with LIL), may be a reflection of; the heightened concerns about the potential of offshoring of "white collar" service jobs or; the increased (and more negative) attention the media has given to globalization (see Marks, Kalaitzandonakes, and Sonduru, 2006).

We combine the answers of these two questions to define a variable that measures whether workers believe they will suffer a pay cut or extended unemployment as a result of job loss. Following Schmidt (1999), we define a binary variable, costly job loss (CjL), as the fraction of respondents who said they were very or fairly likely to lose their job in the next year and also said it would not be easy at all to find another job with similar pay and benefits. We assume workers are indifferent between two jobs with similar pay and benefits, as both jobs would provide the same level of economic security. Although summarizing the survey's information in such categorical variables is far from ideal, there are few alternatives.

3.2 Variables to capture offshoring

Theory indicates that tradable industries will exhibit more-elastic labor demands, rasing labor-market volatility. According to the findings of Kletzer (2007), this is exactly the case. Tradable industries have notably higher job-loss rates than those safe from offshoring; 0.126 compared with 0.058. Additionally, workers in tradable industries saw income loss of $5,453 compared with $2,003 in nontradable industries (as noted in table 1). These findings support the theory that workers in industries safe from offshoring will express significantly lower levels of economic insecurity. Following the results of Jensen and Kletzer (2005), we construct our offshoring variables.[11]

To develop an empirical approach identifying work activities that can be potentially offshored, Jensen and Kletzer assume activities traded domestically can be potentially traded internationally, even if they currently are not. Using spatial clustering, they group industries and occupations into "Gini classes," where those industries and occupations with Gini coefficients less than 0.1 are classified as "Gini class 1" or nontradable. We base our construction of our two offshoring variables on their results.[12] The variable $pIND$ identifies those industries in which activities can be offshored. Industries such as personal services

[11]See Jensen and Kletzer (2005) for further discussion of the methodology used to identify tradable industries and occupations.

[12]The GSS reports respondents' Census industry and occupations codes, while Jensen and Kletzer use NACIS and Major Standard Occupations Classification codes; therefore we use our best judgment to apply their results.

(e.g., teeth cleaning) are coded as zero, or nontradable. There is no reason a dentist or hygienist would worry about their job being offshored. Other industries in which the work could feasibly be offshored are coded as 1.

Similar to our $pIND$ variable, we use Jensen and Kletzer's results to construct a variable pOC, identifying those occupations safe from offshoring (e.g., judges or physicians) and coding the variable as zero; those that can be potentially offshored are initially coded as 1. Certain occupational groups, such as administrative assistants, find themselves in safe industries, but are in an occupation that could be offshored.

3.3 Measuring skill specificity

Between January 2000 and January 2006, over 3 million manufacturing jobs were destroyed while some 8 million new jobs were created in the service sectors of the economy. Transferable skills play an important role in workers' transitions from one industry to another. Some workers' skills are industry-specific, such as machine operators, while other workers have skills that are easily transferable across industries, such as management positions. Workers in occupations with more transferable skills should be less vulnerable to industry-specific shocks than workers with industry-specific skills. As it relates to our offshoring variables, workers with industry-specific skills would expect to see their human capital (and therefore wages) drop more after moving into a new sector than a worker in an occupation with skills that are less industry-specific (more transferable). Bardhan and Tang (2006) suggest calculating an occupational dispersion measure to proxy industry-specific skills. Occupations that are well diversified across industries should exhibit lower levels of industry-specific skills compared with those occupations that are highly concentrated within one industry. They find that an occupation spread out across many sectors is less volatile in terms of wages and employment. We construct a normalized *Herfindahl-Hirshman Index*, HHI^n, to measure worker concentration within industries:

$$HHI_i^n = \frac{\left(\sum_{j=1}^{n} s_{i,j}^2\right) - \frac{1}{n}}{1 - \frac{1}{n}}\ , \tag{11}$$

where $s_{i,j}$ is the share of respondents in occupation i in industry j, n is the total number of respondents, and HHI_i^n ranges from 0 to 1.

Table 2 shows the average value of the HHI_i^n based on 19 major occupational groups for different time periods over the entire sample. All of the occupations tend to stay close to their 77-06 values, regardless of the time period. The last column in the table shows the results of Bardhan and Tang (2006) for 1999 and 2005 using the much larger BLS *Occupational Projections and Training Data*, which averages about $165,000$ employees per occupation.[13] Combining pOC and HHI^n as follows,

$$pOC_i^* = \begin{cases} pOC & \text{if } pOC = 0 \\ 1 - HHI_i^n & \text{otherwise.} \end{cases} \tag{12}$$

[13]The authors thank John Tang for graciously sharing his results with us.

The variable pOC^* addresses the nonlinearity in measuring the impact of offshoring by occupation. For example, a judge or a priest may be in a highly concentrated occupation, but safe from offshoring. Therefore we would expect a respondent to express a high level of insecurity in the face of an industry-specific shock, such as offshoring, only if *his* specific job is prone to offshoring and is in highly concentrated occupation. Workers in safe occupations are coded as zero, and those prone to offshoring are measured by their level of transferable skills.

3.4 Individual fixed effects control variables

Demographic control variables are likely to account for some of the variation among individuals' perceptions about their economic security. However, immeasurable and/or unobserved differences that are specific to individuals may also matter. When answering the GSS survey question about finding a new job, one respondent may believe he could find a new job paying 10 percent less with comparable benefits and answer "somewhat easy," while another respondent may be in the same situation and say "not easy at all." Unlike the U.K. panel survey data used by Scheve and Slaughter (2004) and Campbell et al.(2007), the GSS is a time series of cross-sections that does not track the same individual over different years. We are unable to control for individual-specific effects using the standard practice.[14] However, we have auxiliary data from the GSS survey to approximate the existing individual bias beyond our demographic controls.

Campbell et al. (2007) find that current expectations of unemployment are associated with prior experiences of unemployment. Similary, the GSS asks respondents a question about their *past* financial situation, specifically: "During the last few years, has your financial situation been getting better, worse, or has it stayed the same?" We code the respondents' answers to these questions with values ranging from 1 to 3, where 3 equals getting better. Using this coding, we construct the variable $fSit$. Including this variable in our models allows us to approximate unobserved effects that influence the respondents' answers to the economic insecurity questions. More specifically, $fSit$ can be thought of as a proxy for the past employment situation of the respondent. By definition we assume this variable is exogenous. Including this variable in our estimation produces more precise estimates, but by no means accounts for all the unobserved individual effects that are possible in a panel structure.

4 Empirical strategy

In section 4.1, we analyze the pooled time series cross-section GSS data using probit models, so as to examine the variation in economic insecurity at the individual-respondent level. In section 4.2, we regress the estimated probabilities of a worker expressing costly job loss on the demand for social insurance, as to test the expected utility model results. Included in these regressions is

[14] Starting in 2008 the GSS will switch from a repeating cross-section design to a combined repeating cross-section and panel-component design. When these new data become available they will allow future research to test our approach of controlling for individual-specific effects.

a bias measure that filters individuals sentiment toward government spending independent of labor market concerns.

4.1 Determinates of economic insecurity

In cases where the variable to be estimated is limited to a range of values and contains discrete responses, probit models are employed to provide the best estimation. Generally speaking, we specify a probit model with the same form as Aaronson and Sullivan (1998); Schmidt (1999). However there are a few differences; both authors include a vector of industry variables while our model includes the offshoring variables, and in light of the recent work by Campbell et al. (2007) we control for the respondents past financial situation.

Table 3 reports the coefficients and standard errors from the specifications that use CjL as the dependent variable. The results are reported relative to the base-case; white, male, age 25 to 39, who lived in the northeast in 1988 and worked in an industry and occupation safe from offshoring. For robustness purposes, the first four columns use different model specifications, which include year and regional effects. The fifth column reports the base-case probability and the marginal effects that correspond with the parameters estimated in our "preferred" model 4. This model controls for the respondents' past financial situation, $fSit$. The marginal effect corresponding to this variable indicates that a base-case respondent who indicated his past financial situation has been getting worse is 1.2 percent more likely to express fear of a costly job loss than a worker who believes his financial situation has been getting better. This finding is consistent with Campbell et al. (2007), who find that (for the United Kingdom) an additional 100 weeks of previous unemployment raises the probability of an employee feeling that future unemployment is "likely" or "very likely" by 4 percent. The coefficient on the regional unemployment rate is consistently positive and significant and indicates that a 1 percent increase in the regional unemployment rate will increase workers' perceived economic insecurity by 1.2 percent. This also supports CIR's conclusion that objective labor market indicators are good estimates of workers perceptions, although they may be systematically biased downward.

The variable that has the greatest impact on our insecurity measure is self-employment. If the base-case respondent is self-employed, his probability of expressing costly job loss increases from 5 percent to around 9 percent. If an entrepreneur looses his job, in all likelihood he went out of business, so it is understandable why self-employed workers will express a greater fear of job loss.

The parameter estimates of our offshoring variables are quite robust across all model specifications. Our potential for offshoring variables, $pIND$, pOC, and pOC^* are positive and significant across all model specifications. Model 4 predicts that the probability that the base-case worker will express costly job loss if he works in a tradable industry and occupation would be approximately 7 percent, or 2 percent higher than the base-case. This lends support to our hypothesis that employees in industries and occupations safe from offshoring will express lower levels of job insecurity, and, moreover, that workers in highly diversified occupations express less job insecurity.

4.2 Economic insecurity and the demand for social insurance

Using the base-case probabilities of costly job loss we can re-estimate the tax rates outlined in table 1. The probit model results indicate that the probability a worker in a tradable industry will express fear of costly job loss is 9.2 percent, compared with 6.7 percent in nontradable industries in 2004. These correspond to optimal tax rates of 2.45 percent and 0.88, respectively—which are slightly higher than the optimal tax rates estimated using the actual proportions of the population who experienced costly job loss. Suggesting that workers are, in fact, more pessimistic about their prospects of future job loss and are willing to pay higher tax rates than objective measures would indicate. On the aggregate, the federal government would incur annual costs of about $30 billion. The vast majority of the costs ($25.5 billion) are from providing wage insurance to workers in tradable industries. These number seem reasonable when compared with estimates by Bradford, Grieco, and Hufbauer (2006) that the lifetime loss by workers displaced from offshoring is about $50 billion per year.

While it may seem unreasonable to use the probability of a worker *expressing fear* of a costly job loss as the *actual* probability of costly job loss, we have two justifications for this claim. First, the number of workers that fear costly job loss should be a good approximation of the actual probability a worker will experience a costly job loss. Not all workers who fear costly job loss will actually lose their job; on the other hand, some workers will experience a costly job loss without predicting it. Our estimates of costly job loss for 2002 (8.3 percent and 6.6 percent) compare reasonably well to the proportion of workers who actually experienced costly job loss 2 years later.[15] Moreover, Campbell et al. (2007) find that expectations data are additionally informative and contain useful private information for predicting future unemployment, above and beyond observed objective variables. In light of a more desirable method of estimating the probability of a worker experiencing costly job loss we are left with using these estimated probabilities or the actual proportion of workers who experienced a costly job loss from the DWS.

Unlike the data used by Mughan (2007), which encompasses only one year and two policy questions,[16] the GSS provides us with more questions that allow us to determine whether a link from increased insecurity to greater demands for social insurance truly exists. The GSS asks respondents if they believe the government ought to reduce income differences between rich and poor by raising taxes of wealthy families or by giving income assistance to the poor. This question is comparable to the question used by CIR. Additionally, the survey ask respondents their opinions on the amount of government spending directed toward education, social security, healthcare, and welfare programs. The mean values indicate that, with the exception of welfare, respondents would like to see

[15] Ideally we would like to have the probabilities for 2003, as the survey questions ask respondents "over the next 12 months." However the DWS and the GSS are reported in even years.

[16] Mughan (2007) uses survey questions that ask respondents (1) "Is it the responsibility of governments to take care of people who can't take care of themselves?" and (2) "Do you favor or oppose national health care insurance financed by tax money paying for most forms of health care?"

the federal government direct more money toward dealing with inequality and providing more for education and social security and healthcare.

Model specification (1) in tables 4 through 8 presents the linear regression results between the government spending variables and our estimated probabilities of expressing costly job loss, $\hat{p}_i = prob\,(CjL = 1)$. Model specification (3) includes the respondents wealth on the right-hand side.[17] Unfortunately the GSS asked respondents only to report their wealth in 2006; we therefore present the results using only 2006 data. Where the entire sample was available, model specifications (1) and (2), the results are qualitatively similar.

As expected by the Rodrik (1997) hypothesis, workers with higher levels of insecurity tend to believe the government should dedicate more resources toward reducing inequality. Contrary to Mughan (2007): Higher levels of insecurity are positively correlated with increased spending for welfare and healthcare. Quite surprising, a higher probability of a respondent expressing costly job loss is not correlated with an increase in that respondents support for more money for education. In general, the results lend some support to our hypothesis; however we cannot make any strong assumptions about this link because of the unobserved bias, as we cannot control for individual fixed effects. High-income individuals may be less likely to support government programs because they believe the tax burden will fall on them. Or more insecure individuals tend to have lower skills, and education and earn a lower wage and therefore are more likely to support increased government spending. Conversely, individuals may have an ideological bias where they consistently believe the government spends too much or too little money. Mughan (2007) uses party affiliation as a proxy for this bias; political party affiliation is obviously a function of labor market considerations, among other things, raising an endogeneity problem.

In order to control for the inherent bias in respondents answers, we exploit the data-rich GSS. In addition to questions about funding for social insurance type programs, the GSS asks respondents their opinions about the level of spending to do the following: protect the environment, help cities, reduce crime, reduce drug addiction,provide foreign aid, improve roads, and maintain national parks.[18] We use these questions as instruments to measure the respondents' inherent bias for more or less government spending. None of these variables are correlated with workers insecurity, and theoretically they should not be correlated with employment outlook, but they are highly correlated with the social insurance funding questions.[19] We use these survey questions to calculate individual bias

[17] The variable w is the respondents wealth relative to their total income. Using total wealth as opposed to a proportion does not have a significant impact on the coefficient on $\hat{p}$.

[18] The selection criteria for these variables was exhaustive, first we collected all of the questions related to government funding and created a vector of control variables. Those variables that were correlated with CjL were omitted, as well as any variables that may be affected by changes in the labor market.

[19] One could make the case that poorer workers are more likely to be insecure about their jobs and also more likely to be directly affected by drugs and crime, and therefore support increased funding for these types of programs. This method of filtering could over-estimate the bias factor, but it is unlikely to be an underestimate.

toward more or less government funding by

$$Bias_i = \frac{1}{j}\sum_{k=1}^{j}\left[c_{ik} - \frac{1}{n}\sum_{i=1}^{n} c_k\right] \ , \qquad (13)$$

where c is the vector of control questions. In model specifications 2 and 4 we include $Bias$ on the right-hand side. In all of the models the coefficient on $Bias$ has the expected positive sign and is significant at the 99 percent level. The decline in the predictive power of p and w is insignificant; there continues to be a positive relationship between higher levels of insecurity and increased funding for welfare and an increased role for the federal government in reducing inequality. Taken together the results tend to substantiate the hypothesis that workers with higher levels of insecurity demand more funding for social insurance programs, particularly welfare and reducing inequality even after controlling for individual bias. On other hand, our results do not indicate that insecure workers want the government to dedicate more funding toward long-term solutions that should naturally reduce inequality (and insecurity), such as more money for education, but would prefer direct redistribution of income from the rich to the poor.

5 Conclusion

The data support the hypothesis that increased competition from foreign labor—offshoring, in particular—has played a significant role in generating worker insecurity. While this finding is not necessarily new (for the U.K. see Scheve and Slaughter, 2004), this paper is the first to use U.S. data to analyze this issue. Secondly, Rodrik (1997) and Agell (1999) suggest that rising economic insecurity has increased workers' demand for social insurance. Mughan (2007) and Cusack, Iversen, and Rehm (2006) are the only papers, to our knowledge, to empirically test this hypothesis, and present mixed results. The GSS contains characteristics similar to both studies, and our findings tend to refute those of Mughan (2007) and corroborate the findings of CIR—that objective measures of insecurity play a significant role in forming perceptions and higher levels of insecurity (objective or perspective) cause workers to demand more social insurance. In the process, we substantiate the recent finding of Campbell et al. (2007) by showing that respondents' past financial situation plays a significant role in forming expectations of future job loss.

We have; used an expected utility model to show why higher levels of insecurity should lead to a greater demand for social insurance and; estimated the costs of a wage insurance program. The model predicts that the cost of providing wage insurance to all workers is around \$30 billion. These costs are much higher than the \$16.7 million in wage insurance benefits paid to workers in 2006 through the U.S. Trade Adjustment Assistance program.[20] This program has stringent requirements that requires workers certify (on a layoff-by-layoff approach) that

[20] According to the GAO (2007) only 6,313 workers recieved wage insurance benefits in 2006.

they have been adversely affected by international trade, requirements that drastically increase overhead costs.[21] The wage insurance benefit is only for workers 50 and older who find re-employment within 26 weeks after being laid off from a firm where a significant portion of the affected workers lacked easily transferable skills. Our results suggest that workers with easily transferable skills will not have a hard time finding a job with similar pay and benefits and therefore will not demand wage insurance, making this requirement difficult to test and unnecessary.[22] From one perspective, providing wage insurance to all workers seems like the best approach to increasing participation; workers in tradable industries and occupations with high levels of industry-specific skills will naturally consume the majority of the benefits. Moreover, a wage insurance program could be desirable substitute for unemployment assistance because it reduces the duration of unemployment. Reducing unemployment assistance (which had total outlays of over $30 billion in 2006) or diverting resources from protectionist policies (the annual maximum spending on farm subsidies is $23 billion) will pay for such a program.

We have shown that, because of adverse selection, private markets are not likely to accommodate the demand for wage insurance. Agell (1999) notes that if governments are unwilling and/or unable to address these demands, workers will seek protectionism as a method for relieving their insecurity. Recognizing the rise in worker insecurity and addressing the increased demand for social insurance is an important step toward preventing protectionism and preserving future globalization. We leave it to future research to test whether workers that express higher levels of insecurity actually prefer protectionism over free trade.

[21] According to the GAO (2007), a worker (or group) must first file a petition with the Department of Labor (DOL). Next, the DOL surveys the firm undergoing the layoff and its customers and reviews industry data to determine if the worker (group) meets the criteria for TAA.

[22] The GAO (2007) also recomends that these certification restrictions be eliminated to increase enrollment. The report also notes that workers must forgo training and unemployment insurance benefits to qualify for wage insurance.

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Figure 1: Percent of workers who believe they were likely to lose their job in the next 12 months (95% confidence intervals)

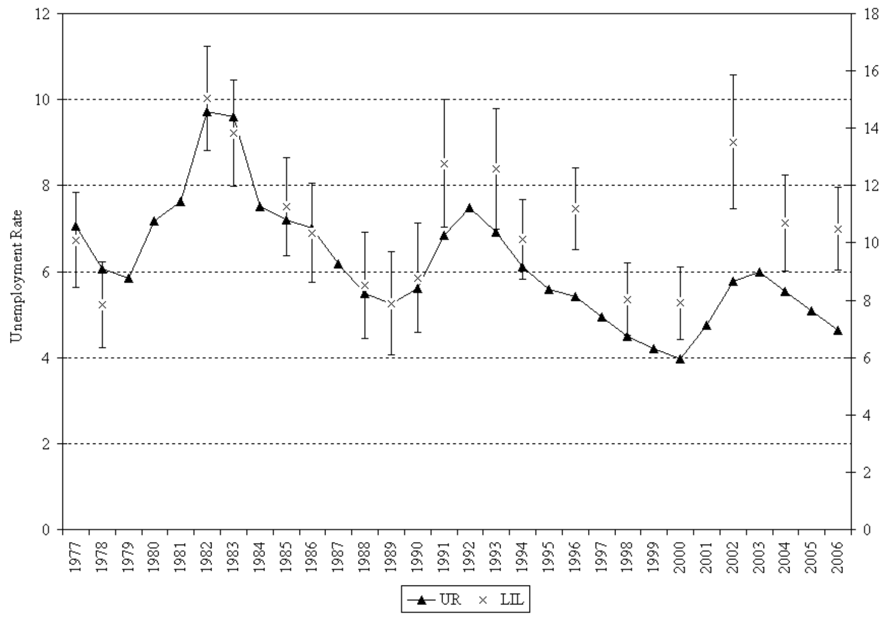

Figure 2: Percent of workers who believe it would be hard to find a job with similar pay or benefits (95% confidence intervals)

Table 1: Model Results

Variable	tradable	nontradable
$\hat{p}$	0.086	0.036
W	$\$20,459$	$\$15,335$
$\delta = b$	$\$5,453$	$\$2,003$
$\overline{W} = W - p\delta$	$\$19,989$	$\$15,262$
t	0.0229	0.0047
Employment (2004)	$139,242,000$	
Employment Share	0.392	0.608
Total Cost	\$25.5 bil	\$6.1 bil

Source: authors' calculations and Kletzer (2007, Tables 7 and 9), employment data are from Bureau of Labor Statistics

Table 2: Industry diversification by occupational group

	$\mathbf{HHI}^n$				**Bardhan and Tang**
Years	*77-86*	*87-96*	*97-06*	*77-06*	*99-05*
Mean	0.294	0.287	0.338	0.290	0.386
Std Dev	0.321	0.302	0.342	0.313	0.319
N	5914	7872	8311	25374	$123.98mil$

Note: Bardhan and Tang data are for the entire labor force.

Table 3: Regression Results: Costly Job Loss

Regressor	**Parameter Estimate**				**Marginal Effect**
Model	(1)	(2)	(3)	(4)	$CjL = 1$
$Intercept/BaseCase$	−2.584* (0.2008)	−2.9081* (0.2566)	−2.9103* (0.2567)	−3.112* (0.2664)	0.0504
$pInd$	0.1673* (0.0424)	0.1736* (0.0427)	0.1746* (0.0426)	0.1778* (0.0434)	0.0171
pOC	0.1009* (0.0417)	0.0957* (.0421)	–	–	–
pOC^*	–	–	0.1044* (0.0457)	0.1205* (0.0467)	0.0116
$Educ$	−0.0605* (0.0070)	−0.0623* (0.0072)	−0.0621* (0.0072)	−0.0521* (0.0074)	−0.0057
UR	0.1050* (0.0092)	0.1263* (0.0175)	0.1263* (0.0175)	0.1242* (0.0176)	0.0120
$fSit$	–	–	–	0.0638* (0.0225)	0.0061
$Female$	−0.0006 (0.0405)	−0.0026 (0.0478)	−0.0035 (0.0409)	−0.0199 (0.0416)	−0.0019
$Under25$	−0.1516* (0.0756)	−0.1362 (0.0760)	−0.1367 (0.0760)	−0.1128 (0.0769)	−0.0109
$35to44$	0.0863 (0.0498)	0.0760 (0.0503)	0.0759 (0.0503)	0.0772 (0.0512)	0.0074
$45to54$	0.0280 (0.0567)	0.0177 (0.0564)	0.0176 (0.0574)	0.0072 (0.0588)	0.0007
$Over55$	0.0046 (0.0690)	0.0034 (0.0697)	0.0036 (0.0697)	−0.0159 (0.0711)	−0.0015
$Black$	0.3648* (0.0498)	0.3493* (0.0514)	0.3493* (0.0514)	0.3503* (0.0524)	0.0337
$Other$	0.2393* (0.0813)	0.2497* (0.0835)	0.2504* (0.0846)	0.2278* (0.0872)	0.0219
$SelfEmpl$	0.4152* (0.0784)	0.4227* (0.0790)	0.4231* (0.0790)	0.4471* (0.0815)	0.0430
Year Effects	No	Yes	Yes	Yes	Yes
Regional Effects	No	Yes	Yes	Yes	Yes
Log Likihood	−2430	−2405	−2405	−2329	−2329
N	13345	13345	13345	12686	12686

Notes: Each cell reports the maximum likelihood parameter estimate and, in parenthesis, its standard error. Base case is a white male, married, age 25-24, living in New England in 1988 and is not self employed.
* Significant at the 95 percent level.

Table 4: Regression Results: Inequality

Regressor	Parameter Estimates			
Model	(1)	(2)	(3)	(4)
Intercept	−4.1264* (0.1375)	−4.104* (0.1352)	−3.9947* (0.1465)	−3.9792* (0.1440)
$\hat{p}$	11.1906* (3.3588)	10.5228* (3.3012)	10.0773* (3.3720)	9.5079* (3.3156)
Bias	–	1.1963* (0.2537)	–	1.1711* (0.2529)
w	–	–	−.00038** (0.0001)	−0.0035** (0.0001)
R^2	0.0190	0.0557	0.0298	0.0650

Note: All regression use 2006 data (N=575). Each cell reports the parameter estimate and, in parenthesis, its standard error.

* Significant at the 99 percent level.

** Significant at the 95 percent level.

*** Significant at the 90 percent level.

Table 5: Regression Results: Welfare

Regressor	Parameter Estimates			
Model	(1)	(2)	(3)	(4)
Intercept	−1.8600* (0.0589)	−1.8513* (0.0583)	−1.8290* (0.0630)	−1.8239* (0.0623)
$\hat{p}$	3.1498** (1.4367)	2.9232** (1.4219)	2.8892** (1.4479)	2.6948*** (1.4331)
Bias	–	0.4083* (0.1093)	–	0.4025* (0.1094)
w	–	–	−0.0000 (0.0000)	−0.0000 (0.0000)
R^2	0.0084	0.0322	0.0117	0.0348

Note: See table 4 (N=570).

Table 6: Regression Results: Social Security

Regressor	Parameter Estimates			
Model	(1)	(2)	(3)	(4)
Intercept	−1.5347* (0.0454)	−1.5278* (0.0448)	−1.5142* (0.0485)	−1.5102* (0.0479)
$\hat{p}$	3.4888* (1.1084)	3.2938* (1.0942)	3.3202* (1.1168)	3.1507* (1.1026)
Bias	–	0.3410* (0.0841)	–	0.3373* (0.0842)
w	–	–	−0.0000 (0.0000)	−0.0000 (0.0000)
R^2	0.0177	0.0461	0.0202	0.0480

Note: See table 4 (N=553).

Table 7: Regression Results: Education

Regressor	**Parameter Estimates**			
Model	(1)	(2)	(3)	(4)
Intercept	-1.3112^{*}	-1.3016^{*}	-1.3012^{*}	-1.2955^{*}
	(0.0395)	(0.0382)	(0.0423)	(0.0409)
$\hat{p}$	1.3267	1.0740	1.2407	1.0222
	(0.9627)	(0.9321)	(0.9719)	(0.9409)
Bias	–	0.4531^{*}	–	0.4518^{*}
		(0.0716)		(0.0717)
w	–	–	-0.0000	-0.0000
			(0.0000)	(0.0000)
R^2	0.0033	0.0691	0.0041	0.0694

Note: See table 4 (N=570).

Table 8: Regression Results: Healthcare

Regressor	**Parameter Estimates**			
Model	(1)	(2)	(3)	(4)
Intercept	-1.3473^{*}	-1.3378^{*}	-1.3529^{*}	-1.3472^{*}
	(0.0402)	(0.0390)	(0.0430)	(0.0417)
$\hat{p}$	1.9482^{**}	1.6958^{***}	1.9951^{**}	1.7738^{***}
	(0.9815)	(0.9530)	(0.9907)	(0.9615)
Bias	–	0.4412^{*}	–	0.4431^{*}
		(0.0730)		(0.0731)
w	–	–	-0.0000	-0.0000
			(0.0000)	(0.0000)
R^2	0.0069	0.0673	0.0072	0.0348

Note: See table 4 (N=567).