# Welfare-Based Income Insecurity in the US and Germany: Evidence from Harmonized Panel Data

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**Abstract**

This paper develops normative approaches for measuring individual-level income insecurity. Using concepts derived from Expected Utility Theory and Prospect Theory, we build a suite of measures designed to capture various facets of psychologically distressing income risk. We present an application for the US and Germany from 1993-2013, employing conditionally heteroskedastic fixed-effects models to generate predictive densities for future incomes. Our results reveal much higher levels of income risk in the US relative to Germany, which can be mostly attributed to a higher level of autonomous, time-invariant volatility. State-by-state variations in liberal/conservative political administrations partially explain our results, and we find some evidence that trade exposure is a contributing factor in the US.

**JEL Classification**: D31, D63

**Key Words**: Economic Insecurity, Income Risk, Panel Data, Reference Dependent Utility

## 1 Introduction

There is an emerging sense of agreement amongst academics, social commentators and the popular press that we are living in insecure economic times. The crisis of 2008 and subsequent global contraction brought long-lasting unemployment to many developed countries, while pressures from globalization, less extensive social safety nets and the lighter regulation of labor markets have left

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many vulnerable to economic shocks. This sense of instability is widespread, and likely to be impacting negatively upon wellbeing. Survey data show that economic risks rank amongst the biggest worries that people face in life, and feelings of insecurity have been linked to increasing morbidity[1] and mortality (Case and Deaton, 2015), as well as rising political populism in the US and Europe (Inglehart and Norris, 2016; Walley, 2017). Indeed alongside various social factors, it is frequently argued that economic insecurity is a key driver of the widening cultural schisms now observed in many Western countries.[2]

In this paper, we develop econometric techniques for modeling insecurity as unpredicted volatility in future incomes, and use these techniques to study emergent patterns across the United States and Germany. Our methodological approach is designed to capture psychologically damaging income risk at the individual level. By combining features from existing models with concepts borrowed from the inequality and behavioral literature, we produce indices that resolve several important conceptual issues. Our method involves estimating (in panel data) predictive densities for each individual one year into the future. Foreseeable *ex ante* fluctuations are reflected in changes in the conditional mean, while unforeseeable volatility is determined by the variance, which is parameterized as a function of both fixed and time-varying covariates. From this model, we show that intuitive normative risk measures based upon Expected Utility Theory (EUT) have simple closed-form expressions. Further, since Reference Dependent Utility (RDU) functions employed in Prospect Theory can better reflect psychological responses to risk (e.g. Di Tella *et al.*, 2010), we support the EUT metrics with additional indices built upon this concept.

The second objective is to study patterns of insecurity across our two countries. As the US and Germany differ sharply in terms of the social insurance mechanisms they provide, our analysis sheds new light onto the ways that policy affects micro-level economic risk. In particular we study

[1] Related research connecting economic risks and health include Berloffa and Modena (2012), Catalano (1991), Kong *et al.* (2019), Offer *et al.* (2010), Reichert and Tauchmann, (2017), Rohde *et al.* (2017), Watson and Osberg (2017) and Staudigel (2016). Other studies highlight the negative effects of insecurity on wellbeing (Clark *et al.*, 2010), the degradation of familial relationships (Hardie and Lucas, 2010) and other health behaviors such as smoking (Barnes and Smith, 2009).

[2] Edsall (2017) is a typical example. The hypothesis is that economic security is an essential input for the adoption of *postmaterialistic* cultural values (Inglehart, 1977) which emphasize diversity and self expression over monetary concerns. A polarized distribution of economic risk may therefore allow a secure subset of a population to develop these values while less secure subsets do not.

(i) how the relative levels of insecurity differ across our two countries, and (ii) the factors that have been driving changes over time.

To foreshadow our main findings, we observe that despite a higher mean income and lower level of intertemporal mobility,[3] insecurity is much higher in the US than Germany. This result mainly stems from a greater level of autonomous variance in forecasts for log income. Our models therefore attribute the differential to ingrained (invariant over time and over individuals) country-specific phenomena, which suggests that differing institutional environments are likely to be ultimately responsible. Indeed, it appears that the relatively strong labor laws and broad social safety nets in Germany have been very effective in mitigating insecurity.

In terms of trends, our indices increased steadily in the US, a finding that matches the popular narrative of increasing economic anxiety. Conversely no comparably robust result for Germany appears, which also seems consistent with anecdotal evidence. US insecurity also increased much more sharply for households exposed to global trade (there is no such relationship for Germany), which supports the hypothesis that globalization may be a significant source. Lastly, we linked our data with changes in the policy environment by examining whether the partisan affiliations (i.e. liberal or conservative) of state governments could explain some of our trends. Insecurity does appear to rise after administrations switch from liberal to conservative, although the effect size is small and not especially robust.

Our work adds to a growing body of research that models important aspects of individual or household-level economic risk (Bossert and D'Ambrosio, 2013; 2016; Burgess *et al.*, 2000; Calvo and Dercon, 2005; Cunha and Heckman, 2016; Feigenbaum and Li, 2015; Hacker, 2006; Hoddinott and Quisumbing, 2003; Western *et al.*, 2012). However due to the complexity of this task, there has been little consensus about how to appropriately measure stress-inducing income risk. For example, sharp declines in income may be a source of anxiety if they are unexpected, or occur near to the poverty line, or they may have no adverse effects if anticipated or the result of transitory

[3] See Bayaz-Ozturk *et al.* (2014) and Burkhauser and Poupore (1997).

mean-reversion. Other issues related to the distinction between *ex ante* risk (the threat of experiencing either poverty or a meaningful loss in the future), and *ex post* volatility (having had an income stream that was variable in the past). By using regression models to filter out predictable variations, and by employing forecasting methods to model risk *ex ante*, our paper produces measures that correspond much more closely with conceptual definitions of insecurity (Osberg, 1998; Western *et al.*, 2012) than previous works (e.g. Rohde *et al.*, 2015).

The paper is structured as follows. Section 2 specifies the models and derives the risk indices, while Section 3 presents the bulk of the empirical analysis, including the cross-national comparisons. Section 4 summarizes and concludes. Some supplementary materials (descriptive statistics; distributions of our measures; time-trends) are presented in the appendix.

## 2 Income Insecurity in Panel Data

A wide variety of tools have been developed for studying dynamics in outcomes such as income, earnings, consumption or wealth. Some of the existing techniques are fairly simple - for example there are descriptive measures developed by Hacker (2006), who identifies downside risk by quantifying drops in income of 25% or more; Ziliak *et al.* (2011), who employ the arc intertemporal percentage change in incomes; and Gottschalk and Moffitt (2009) who use decompositions based upon the variance. Other authors employ more complex error component or ARIMA specifications (e.g. Moffitt and Gottschalk, 2012; Meghir and Pistaferri, 2011) to separate incomes into permanent and transitory components, where the latter forms an indicator of short-run instability.[4] An advantage of these approaches is that they allow for neat decompositions of inequality, however they lack the features we require for isolating potentially stressful forms or risk exposure.

[4] The canonical model is usually applied to labor income and of the form $y_{it} = \mu_i + v_{it}$ where earnings is measured in logs, and an individual is characterized with a permanent income $\mu_i$ and a transitory component $v_{it}$ . This allows for the simple inequality decomposition $\sigma_y^2 = \sigma_\mu^2 + \sigma_v^2$ .

Our method differs from the more descriptive approaches in that it places a substantial structure on the income generating process, which allows us to better understand the roles that covariates play in producing and sustaining downside risk. We begin by considering individual $i$ in time $t$, who is worrying about their income in $t+1$. As this future value is unknown, the individual is exposed to a potentially stress-inducing economic risk. Under this framework, future incomes are random draws from probability density functions with means and variances tailored to reflect each individual's idiosyncratic circumstances. Thus we are characterizing insecurity as the unpredictability implicit in a statistical forecasting problem. For simplicity, we use a time-horizon of one year (i.e. the individual is concerned about their transition from $t$ to $t+1$), which corresponds with psychometric evidence on future planning and decision making (Wittman and Paulus, 2009). Our strategy is therefore to use econometric models to approximate short-term risk perceptions; an approach that is reasonable on average but unlikely to hold in all instances. Factors such as specification error, unobservables known to the individual but excluded from our models, or heterogeneous risk preferences, could all result in econometric estimates that do not always directly correspond with subjectively experienced risk.[5]

We begin with a conditionally heteroskedastic log-linear fixed-effects model

$$\ln(y_{it}) = \alpha_i + \mathbf{x}_{it}^{'}\boldsymbol{\beta} + \varepsilon_{it} \qquad \varepsilon_{it} \sim \mathcal{N}\left(0, \sigma_{it}^2\right), \qquad \sigma_{it}^2 = \exp\left(\gamma + \mathbf{z}_{it}^{'}\boldsymbol{\theta}\right) \tag{1}$$

where $y_{it}$ is real household equivalized income, $\mathbf{x}_{it}$ and $\mathbf{z}_{it}^{'}$ are vectors of determinants (one of which is a time trend), $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ are vectors of parameters, $\alpha_i$ a time-invariant individual-specific effect, $\gamma$ a constant and $\varepsilon_{it}$ a random shock. If an individual knows $\alpha_i$ and their covariate vectors for the coming year (i.e. $\mathbf{x}_{it+1}^{'}$ and $\mathbf{z}_{it+1}^{'}$) this model can provide a point estimate for their future income. However, since insecurity relates to the threat of experiencing an adverse shock, the full distribution of potential outcomes is needed, where the left tail of this distribution will determine downside risk. Since $\varepsilon_{it} \sim \mathcal{N}(0, \sigma_{it}^2)$, we can obtain the complete predictive densities, and as

[5]Hacker (2006) argues that insecurity measures are better interpreted as averages due to individual-specific heterogeneity associated with unobservables and risk preferences.

the dependent variable is in logarithmic form, each outcome $y_{it+1}$ will be lognormal - a common parametric model for the distribution of income.[6]

$$y_{it+1} \sim \ln \mathcal{N}\left(\mu_{it+1}, \sigma^2_{it+1}\right) \Longleftrightarrow f\left(y_{it+1}\right) = \frac{1}{y\sqrt{2\pi \exp\left(\gamma + \mathbf{z}'_{it+1}\boldsymbol{\theta}\right)}} \exp - \left(\frac{\left(\ln\left(y\right) - \alpha_i - \mathbf{x}'_{it+1}\boldsymbol{\beta}\right)^2}{2\exp\left(\gamma + \mathbf{z}'_{it+1}\boldsymbol{\theta}\right)}\right) \tag{2}$$

A key feature of EQ (2) is that both the mean (denoted in shorthand by $\mu_{it}$) and the variance ($\sigma^2_{it}$) can vary over $i = 1, ..., N$ and $t = 1, ..., T$. Thus both the scale and spread can be calibrated to reflect each individual's predicted economic outcomes. The conditional mean is given by $\alpha_i + \mathbf{x}'_{it+1}\boldsymbol{\beta}$ while the variance is $\exp\left(\gamma + \mathbf{z}'_{it+1}\boldsymbol{\theta}\right)$, where the use of the exponential term ensures $\sigma^2_{it} > 0$. We also differentiate notationally between the covariate vector for the mean equation $\mathbf{x}'_{it}$ and the variance equation $\mathbf{z}'_{it}$. Here $\mathbf{x}'_{it}$ can only contain time-varying predictors due to the presence of $\alpha_i$ in the mean function, while $\mathbf{z}'_{it}$ can contain both fixed and time-varying covariates. Subject to this requirement any exogenous predictors of income or its variance may be included (i.e. we do not require exclusion restrictions to identify the model) and the same variables may appear in both equations. Consequently, the range of variables usable in the latter should be larger than in the former (see Section 3 for more on this issue).

The fact that we are able to parameterize both these facets of the model is a substantial advantage over less structured econometric approaches. As the mean can adjust in response to covariates included in $\mathbf{x}'_{it}$ we can filter out the effects of predictable variations as required. This is important since these fluctuations are usually regarded as relatively benign because they can be planned for in advance (Western *et al.*, 2012). Further, our variance term can accommodate differences across individuals, and also adapt as drivers of risk change via $\mathbf{z}'_{it}$. Thus, the ability of this model to separate these types of volatility allows us to isolate or eliminate specific forms of predictive error, while focusing on the types that are likely to cause distress.

[6]See Kleiber and Kotz (2003) for a detailed description of the lognormal for modeling the distribution of incomes. We note that more flexible distributions (e.g. Dagum or GB2) will normally provide a better fit (Jenkins, 2009) at the cost of decreased parsimony. The validity of this functional form can be assessed by examining standardized residuals from the estimated models. In our data we reject the null of lognormality (using Jarque-Bera tests) at all levels for both countries - our data are slightly negatively skewed and have kurtosis exceeding three. However graphical analysis shows that the departures from lognormality are relatively small and rejection is driven mostly by the large sample sizes ($n = 181,567$ for the US and$n = 79,272$ for Germany). The plots are omitted for the sake of brevity but are available upon request.

Estimating EQ (2) is done using maximum likelihood to handle the non-constant variance.[7] To simplify we employ *within* transformations to eliminate $\alpha_i$, and proceed employing our assumption of error normality using the Newton-Raphson algorithm. This allows us to preserve fixed effects when modeling conditional means, but does not incorporate these terms in the variance equation.[8] Once the model is estimated, we recovered the individual-specific terms using $\hat{\alpha}_i = \bar{y}_i - \bar{\mathbf{x}}_i' \boldsymbol{\beta}$ and predictions are generated for the coming year by combining the one-step-ahead covariate vectors $\mathbf{x}_{it+1}'$ and $\mathbf{z}_{it+1}'$ with $\hat{\boldsymbol{\beta}}$ and $\hat{\boldsymbol{\theta}}$. Choosing appropriate values for these vectors represents an established challenge in forecasting as it is likely that other variables will change besides time. However, we use a standard simplifying assumption and only update the time dimension(s). That is, we assume that individuals base their predictions upon their prevailing characteristics, excluding risk attributable to predictable fluctuations in covariates between $t$ and $t+1$. To allow for predictable variations in $\mathbf{x}_{it}'$ to inform our estimates we would require a panel VAR model, which is too demanding to be practical for our data set.[9]

Once a predictive density is estimated for each individual, the distributions may be summarized using any of a number of methods developed in the economics or finance literature. Here we consider two approaches, based on Expected Utility Theory (EUT) and Reference Dependent Utility (RDU) respectively, and outline the techniques below.

[7]Other approaches such as separate estimation of mean and variance equations using Least Squares were also considered. We examined robustness with respect to the estimation framework using the two-step model the two-step model $\ln(y_{it}) = \alpha_i + \mathbf{x}_{it}'\boldsymbol{\beta} + \varepsilon_{it}$, $\ln\left(\hat{\varepsilon}_{it}^2\right) = \gamma + \mathbf{z}_{it}'\boldsymbol{\theta} + v_{it}$ which gave very similar (but non-identical) parameter estimates.

[8]We also rely on large $T$ asymptotics to account for the estimation of individual-specific effects - since $T = 13$ in our panels we argue that this is reasonable, although as a consequence hypothesis tests in our main model will have a slight tendency to over-reject (Cameron and Trivedi, 2005; Chapter 21).

[9] Such an approach would be useful however for models that extend the time dimension (e.g. forecasting from $t$ to $t+2$ to handle longer term risks).

## Methods Based Upon Expected Utility

A standard method for quantifying risk exposure comes from Expected Utility Theory (EUT), which involves specifying $U(y)$ (where $U(y) \geq 0$, $U'(y) > 0$ and $U''(y) < 0$) and comparing the welfare in the predictive distribution, with a degenerate distribution with the same mean. Under this framework, unexpected positive shocks to income will increase welfare, but through the concavity of $U(y)$ (which governs the degree of risk aversion) negative shocks will have larger effects, which will dominate even when the underlying distribution is symmetrical. It is this asymmetric weighting that focuses the measures on downward volatility, and links the concept of unpredictability with insecurity. Related methods have been employed in this context before, most notably by Ligon and Schechter (2003) and Feigenbaum and Li (2015). Let us define $E[U(y_{it+1})]$ as the expected utility of income for the coming year, and $U(E[y_{it+1}])$ as the utility gained if the future value is known with certainty. The certainty equivalent income $U^{-1}(E[U(y_{it+1})])$ and the expected value $E[y_{it+1}]$ are also required. The loss in welfare due to unpredictability in the level of income may be determined using

$$I_{it}^{DN} = 1 - \frac{E[U(y_{it+1})]}{U(E[y_{it+1}])} \qquad\qquad I_{it}^{AT} = 1 - \frac{U^{-1}(E[U(y_{it+1})])}{E[y_{it+1}]}.$$

Both these measures have parallels with the inequality literature. Here $I^{DN} \in [0\,1]$ corresponds to Dalton's (1920) index for the welfare cost of unequal incomes, while $I^{AT} \in [0\,1]$ is analogous to the Atkinson (1970) inequality metric. Both measures are equal to zero if the predictive variance is zero, and via Jensen's Inequality, will take on strictly positive values when $\sigma_{it}^2$ is positive. A neat benefit of the log-linear framework we employ in EQ (2) is that if one is prepared to employ risk preferences implicit in $U(y) = \ln(y)$[10] then the measures have simple closed-form expres-

[10]Logarithmic utility implies decreasing Arrow-Pratt absolute risk aversion ($R_A(y) = -U''(y)/U'(y) = 1/y$) and constant relative risk aversion ($R_R(y) = -yU''(y)/U'(y)) = 1$. Arrow (1965) provides an axiomatic justification for this function. To test robustness we also replicated the analysis for the exponential utility function $U(y) = 1 - \exp(-\phi y)$, where $\phi > 0$ determines risk aversion (Norstad, 2011). Results were similar across the distribution except in the extreme right tail, where larger risk indices were obtained. Levels and trends across the two countries were also unaffected.

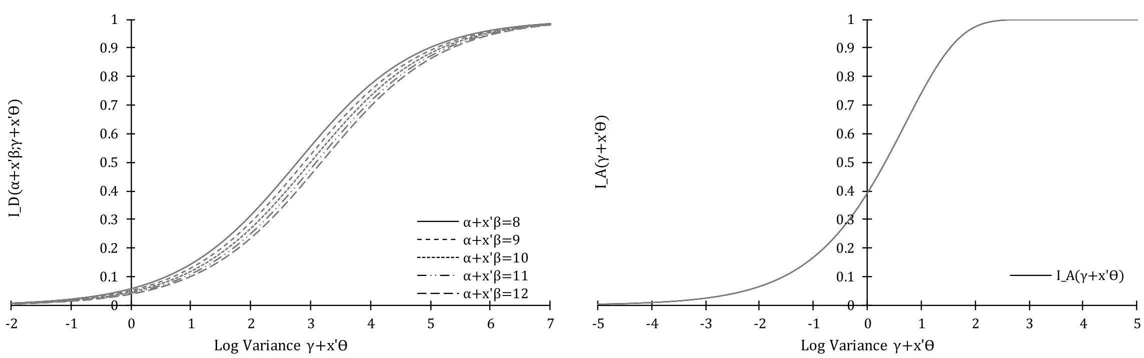
sions. Properties of the normal and lognormal imply $E\left[U\left(y_{it+1}\right)\right]=\alpha_i+\mathbf{x}_{it+1}^{'}\boldsymbol{\beta}$ and $E\left[y_{it+1}\right]=\exp\left(\alpha_i+\mathbf{x}_{it+1}^{'}\boldsymbol{\beta}+\frac{1}{2}\exp\left(\gamma+\mathbf{z}_{it+1}^{'}\boldsymbol{\theta}\right)\right)$, while $U\left(E\left[y_{it+1}\right]\right)=\alpha_i+\mathbf{x}_{it+1}^{'}\boldsymbol{\beta}+\frac{1}{2}\exp\left(\gamma+\mathbf{z}_{it+1}^{'}\boldsymbol{\theta}\right)$ and $U^{-1}\left(E\left[U\left(y_{it+1}\right)\right]\right)=\exp\left(\alpha_i+\mathbf{x}_{it+1}^{'}\boldsymbol{\beta}\right)$. With some algebra, both can be written in terms of the parameters of EQ (2)

$$I_{it}^{DN}=1-\frac{\hat{\alpha}_i+\mathbf{x}_{it+1}^{'}\hat{\boldsymbol{\beta}}}{\hat{\alpha}_i+\mathbf{x}_{it+1}^{'}\hat{\boldsymbol{\beta}}+\frac{1}{2}\exp\left(\hat{\gamma}+\mathbf{z}_{it+1}^{'}{}'\hat{\boldsymbol{\theta}}\right)} \tag{3}$$

$$I_{it}^{AT}=1-\exp\left(-\frac{1}{2}\exp\left(\hat{\gamma}+\mathbf{z}_{it+1}^{'}\hat{\boldsymbol{\theta}}\right)\right). \tag{4}$$

These expressions allow the relative impacts of the mean and variance of log income to become apparent. It is clear that both $I_{it}^{DN}$, $I_{it}^{AT}\rightarrow 0$ if $\hat{\gamma}+\mathbf{z}_{it+1}^{'}\hat{\boldsymbol{\theta}}\rightarrow-\infty$, and each monotonically increases such that $I_{it}^{DN}$, $I_{it}^{AT}\rightarrow 1$ as $\hat{\gamma}+\mathbf{z}_{it+1}^{'}\hat{\boldsymbol{\theta}}\rightarrow\infty$. These behaviors are illustrated in Figure 1 which shows the relationship between the two measures and $\mathbf{z}_{it+1}^{'}\hat{\boldsymbol{\theta}}$.

Figure 1: EUT Insecurity Indices Against Logged Predictive Variance




Note: The left panel shows the relationship between the logged predictive variance and $I^{DN}$ for five different logged conditional means taking integer values from 8 - 12 where lower mean values imply higher curves. The right panel shows the same relationship for $I^{AT}$ which is mean independent.

For $I_{it}^{DN}$ (left panel) the rates of convergence to 0 (incomes are perfectly predictable) and 1 (infinite predictive variance) depend upon the level as captured by individual-specific effect $\alpha_i$ and the time-varying component $\mathbf{x}_{it+1}^{\prime}\hat{\boldsymbol{\beta}}$. This defines insecurity in terms of the threat of future destitution, such that the impact of unpredictable volatility is greater when incomes are lower. Hence the curves with lower means lie above those for the full domain of the function. The affine transformation $U(y) = \ln(y) + c$ for any $c \in \mathbb{R}$ will have a similar effect, and hence this parameter is implicitly set at zero. Conversely $I^{AT}$ (right panel) is simply an increasing function of the forecast variance and invariant to $c$. The index is homogeneous of degree zero in $y$ (leaving only the solitary curve) indicating that insecurity is defined by the unpredictability of future log-incomes. Thus a richer individual can experience just as much of a relative decline in welfare as a poorer person, although increasingly larger shocks are required at higher levels to maintain the same variance in logged outcomes. Given these differing sensitivities to the level of income, $I^{DN}$ and $I^{AT}$ define risks related to absolute shortfalls and relative variations respectively.

### Measures Based on Reference Dependent Utility

A potential criticism of EUT measures is that they tend to align poorly with experimental data on preferences (Barberis, 2013), and hence may not properly capture psychological responses to risk. For example, in developed countries (where absolute material deprivation is rare), individuals may feel more insecure about relative declines in status than the threat of future destitution. The standard assumption of concavity of welfare in income has also been shown to hold for gains, but break down for losses, implying that people experience *diminishing sensitivity* to more extreme outcomes, or alternatively, a preference for the status quo. And individuals are known to exhibit *loss-aversion*, where a loss of some small amount of money is felt much more strongly than an equivalent gain. These violations of EUT are tied together in Prospect Theory (Kahneman and Tversky, 1979) and its various offshoots (such as Cumulative Prospect Theory) which provide a descriptive alternative theory of decision making under risk.

It is straightforward to extend our framework by using Reference Dependent Utility (RDU) functions (Gilboa and Schmeidler, 2001; Maggi, 2004) to construct indices that incorporate key insights from Prospect Theory. Assume that each individual has some psychologically relevant benchmark income level against which losses and gains are defined. Such a system will register positive experiences when incomes increase beyond this value and negative experiences when they fall, and hence an expectation of negative future changes is a way of conceptualizing reference-dependent insecurity. To generate some alternative indices along these lines, we define an individual's current income as their reference point, such that the variable $\tilde{y}_{it} = y_{it+1} - y_{it}$ measures deviations from baseline.[11] A standard parametric functional form is

$$v(\tilde{y}) = \begin{cases} \tilde{y}^{\xi} & \tilde{y} \geq 0 \\ \lambda (-\tilde{y})^{\xi} & \tilde{y} < 0 \end{cases} \tag{5}$$

where $\xi < 1$ and $\lambda < -1$ govern the risk preferences. Parameter $\xi$ controls the degree of concavity/convexity for gains/losses while $\lambda$ provides loss aversion ($\lambda = -1$ implies symmetry between losses and gains). Tversky and Kahneman (1992) generate estimates of $\hat{\xi} = 0.88$ and $\hat{\lambda} = -2.25$ based on experimental data, implying only slight risk aversion (risk seeking) for gains (losses), but losses are more than twice as potent as gains. Using this function, the expected utility of a change in income is

$$\bar{v}(\tilde{y}) = \int_{-\infty}^{0} \lambda (-\tilde{y})^{\xi} f(\tilde{y})\, d\tilde{y} + \int_{0}^{\infty} \tilde{y}^{\xi} f(\tilde{y})\, d\tilde{y}. \tag{6}$$

Two further measures are built upon this concept. The first is relatively straightforward and is simply the negative of $v(\tilde{y})$, giving the expected reference dependent loss in welfare in the coming period. The second assumes that the individual is forward-looking and actively anticipates a change in income from her current level. This measure incorporates baseline effects by assessing the expected utility in EQ (6) against the utility experienced if the individual receives her expected

[11] Note that for convenience in interpretation we measure $\tilde{y}_{it}$ in thousands of dollars.

income in the coming period, given by $v\left(\hat{y}_{it+1} - y_{it}\right)$. The risk measure is therefore defined as the difference in utility between two alternative scenarios. In Scenario A our individual does not know her future income, but does know its distribution and hence is exposed to risk. Scenario B represents a risk-free alternative, and considers what her utility would be if she learned she will receive her econometrically predicted expected income in the coming year. The two measures capturing *expected losses* and unanticipated *reference dependent* change are therefore

$$I_{it}^{EL} = -\bar{v}\left(\tilde{y}_{it}\right) \tag{7}$$

$$I_{it}^{RD} = v\left(\hat{y}_{it+1} - y_{it}\right) - \bar{v}\left(\tilde{y}_{it}\right) \tag{8}$$

Unlike the indices given in EQ (3-4), the reference dependent loss metrics in EQ (7-8) can take on both negative and positive values. If the distribution $f\left(\tilde{y}\right)$ has a large degree of downside risk (i.e. assigns high probabilities for large negative values) both measures will be positive. This makes sense for an insecurity measure as the individual is likely to experience a psychologically painful loss in the coming period. Conversely, if $y_{it}$ is low and $f\left(\tilde{y}\right)$ describes a distribution of mostly positive values, then the individual is likely to experience a gain, and should be regarded as having low (negative) insecurity. An important property of these measures however is that they are sensitive to the scale of the income variable. Since absolute variations in incomes are greater at higher income levels, both indices will be *positively* associated with economic status. Thus unlike $I^{DN}$ and $I^{AT}$ (which capture low-end and scale-free forms of insecurity), these measures are best suited for measuring high-end anxieties - i.e. those associated with declines amongst relatively affluent subsets of society. Analogously, as these declines need not result in deprivation, these measures are more likely to reflect risks to relative status and social rank. As we show in the next section these conceptual differences are important, and empirical results are often sensitive to the type of risk considered.

# 3 Modeling Income Insecurity in the US and Germany

Our empirical application models economic risk in the US and Germany and has three main goals. We focus especially on (i) why the levels are so different across these two countries, (ii) the factors explaining interpersonal differences within each country, and (iii) how insecurity has been changing over time. In particular, we look to contrast the experience of the US which showed high and increasing insecurity across our spectrum of measures, with Germany, where insecurity was low, stable and relatively less strongly stratified across various socioeconomic indicators.

### Data

Data come from the Cross-National Equivalence File (CNEF) which is a collection of harmonized socioeconomic panels adapted from sources such as the PSID (US), SOEP (Germany), BHPS (Great Britain) and HILDA (Australia). Produced by researchers at Ohio State University, the CNEF is specifically designed to allow for meaningful comparisons of incomes, education levels and other key variables across the included nations (Frick *et al.*, 2007). We employ the longest possible panel that is consistent across both countries which runs from 1993 to 2013.[12] Since the US data omit every second year from 1997 onward these waves are excluded for Germany to maintain comparability. Thus we end up with 13 waves for each country spanning 21 years. The length of the panel is crucial in order to minimize bias in the estimation of the individual-specific effects. Although there is no theoretical answer of how large $T$ must be for this purpose, several authors (e.g. Heckman, 1981) argue that values as small as $T = 8$ can be appropriate. In longer panels such as ours, attrition is a potential problem (we do not have access to attrition weights) but we note that the impacts on econometric panel estimates are usually small (Cheng and Trivedi,

[12] Data before 1992 is omitted for Germany due to the reunification of the East and West in 1990, and observations beyond 2013 are not yet available.

2015). Inevitably there may also be slight differences in patterns of attrition and other forms of non-response across the samples.

Our unit of analysis is the individual and the main variable of interest is household post-government income, which is the sum of inflows less taxes for all household members. We use real income throughout and employ PPP exchange rates such that observations for both the US and Germany are measured in 2013 US Dollars. To account for economies of scale within the household, the variable is then standardized using the square-root equivalence scale.[13] Since the objective is to capture household welfare (rather than say labor earnings) we do not impose age restrictions, and as our dependent variable is log-transformed (compressing high values in our regressions) we do not trim very large incomes from our sample.

To model our predictive densities, we take a fairly standard selection of plausibly exogenous covariates. In principle a fully-specified model would contain a rich array of variables capable of predicting all foreseeable fluctuations in expected incomes, and also all factors driving variations in idiosyncratic risk. However due to data availability issues we are constrained to variables that are both commonly measured and also harmonized for the sake of cross-national comparisons. In terms of the mean equations, we use indicators of education, household size and composition, marital status, employment status and working hours, alongside some aggregate covariates to capture macroeconomic factors such as employment rates by regional area and education level, and estimates of average income by state. To model the variance we employ all these variables as well as time-invariant indicators or factors such as race and gender. Descriptive statistics of our samples are presented in Table 5 in the Appendix.

[13]As household membership appears in the denominator of our income measure the variable will be subject to volatility through changes in size or structure.

### Estimation

The models are fitted separately to the US and German data and the results are reported in Table 1, where the coefficients in the mean equation are given in the left columns while the coefficients of the logged variance are in the rightmost columns. Cluster-robust covariance is used where clustering is performed at the individual level. Due to methodological complications that arise in more complicated models we eschew the use of weights (Gellman, 2007; Winship and Radbill, 1994) but note that employing them generally has only minor effects upon our results. We also note that we are assuming a stationary panel, which becomes important as the time dimension becomes large.[14]

The models fit the data well, with pseudo $R^2$ terms (squared correlation between actual and predicted log incomes) for the US and Germany of 0.58 and 0.72 respectively.[15] Given the presence of conditionally dependent heteroskedasticity we also present the likelihood ratio

$$D = -2 \ln \mathcal{L} \left( \boldsymbol{\beta}, \gamma \right) + 2 \ln \mathcal{L} \left( \boldsymbol{\beta}, \boldsymbol{\theta}, \gamma \right) \tag{9}$$

where $D \dot{\sim} \chi^2_v$ tests the restriction $\boldsymbol{\theta} = \mathbf{0}$ via the difference in fit across the heteroskedastic and homoskedastic models. The final row shows that these are well in excess of the 5% critical values of 25.9 and 24.8 and hence we conclude that uneven variances are an important feature of the data in both countries.

[14]As a robustness check we divided our samples into two periods (before and after 2000) and estimated the models separately for each. We find some evidence of parameter heterogeneity across the time periods (especially for the US), but note that the general results with respect to levels and trends of the indices continue to hold for both countries.

[15]We include the individual-specific effects in these calculations.

Table 1: Fixed Effects Income Models with Conditionally Dependent Heteroskedasticity: - US and Germany

| | | United States | | Germany | |
|---|---|---|---|---|---|
| Variable Type | Variable Name | Mean | Log Variance | Mean | Log Variance |
| Individual/Household | Constant | 10.225*** | -0.673** | 9.416*** | -1.496*** |
| | | [0.0405] | [0.2654] | [0.0527] | [0.3305] |
| | Education (Years) | -0.019*** | 0.011 | 0.010*** | 0.024 |
| | | [0.0029] | [0.0164] | [0.0036] | [0.0188] |
| | Married | 0.136*** | -0.171*** | 0.132*** | -0.182*** |
| | | [0.0102] | [0.0485] | [0.0098] | [0.0541] |
| | Separated/Divorced | 0.087*** | 0.046 | 0.055*** | -0.003 |
| | | [0.0138] | [0.0655] | [0.0137] | [0.0756] |
| | Widowed | 0.106*** | 0.195** | 0.061** | 0.099 |
| | | [0.0209] | [0.0984] | [0.0246] | [0.1299] |
| | Household Head | -0.507*** | 0.290*** | -0.212*** | 0.043 |
| | | [0.0103] | [0.0428] | [0.0116] | [0.0502] |
| | Household Size | -0.008*** | -0.037*** | 0.052*** | -0.089*** |
| | | [0.0027] | [0.0115] | [0.0032] | [0.0166] |
| | Children | -0.220*** | -0.102 | -0.482*** | -0.161** |
| | | [0.0156] | [0.0795] | [0.0134] | [0.0843] |
| | Part Time Work | -0.141*** | 0.338*** | -0.045*** | 0.212*** |
| | | [0.0058] | [0.0438] | [0.0050] | [0.0491] |
| | Not Working | -0.443*** | 1.062*** | -0.139*** | 0.570*** |
| | | [0.0106] | [0.0539] | [0.0169] | [0.1126] |
| | Work Hours | 6.8E-05*** | 3.0E-06 | 6.9E-05*** | -9.5E-05*** |
| | | [4.0E-06 ] | [2.3E-05] | [3.7E-06] | [3.4E-05] |
| | Trend | 0.011*** | 0.005 | 0.014*** | 0.016*** |
| | | [0.0004] | [0.0028] | [0.0007] | [0.0051] |
| Aggregate | Employment Rate (by State) | 0.381*** | -0.887*** | -0.271*** | 0.706* |
| | | [0.0411] | [0.3225] | [0.0485] | [0.4217] |
| | Employment Rate (by Educ) | -0.181*** | 0.144 | 0.172*** | -0.416 |
| | | [0.0379] | [0.2159] | [0.0385] | [0.3301] |
| | Per Capita Output (by State) | 9.0E-06*** | -8.0E-06*** | 1.2E-05*** | -1.0E-05* |
| | | [4.9E-07] | [2.95E-06] | [8.3E-07 ] | [6.1E-06] |
| Fixed | Age | | -0.034*** | | -0.066*** |
| | | | [0.0044] | | [0.0082] |
| | Age Squared | | 3.6E-04*** | | 0.001*** |
| | | | [4.5E-06] | | [0.0001] |
| | Female | | 0.010 | | 0.051 |
| | | | [0.0325] | | [0.0368] |
| | Non-White | | 0.312*** | | |
| | | | [0.0305] | | |
| Supplemental | No. Groups | 30257 | | 22430 | |
| | No. Observations | 181567 | | 79272 | |
| | Log likelihood | 42162 | | 85762 | |
| | Pseudo $R^2$ | 0.584 | | 0.720 | |
| | $D$ | 17246 | | 2807 | |

Note: The table provides parameter estimates for EQ (1) for US and German harmonized panel data 1993-2013. The dependent variable is the log of equivalized household income (left columns) and the log of the error variance is presented in the right hand columns. Dummies are defined relative to a reference individual who is unmarried and engaged in full time employment. *, ** and *** denote significance at 10%, 5% and 1% respectively.

Examining the parameter estimates, we see that the coefficients are generally in line with expectations, and are broadly consistent across the countries. In the mean equations, being married, working full time and living in a richer state predict higher incomes, while working part time, having otherwise limited working hours, or living in households with multiple children predict lower outcomes. The coefficients on education are small/negative as the benefits accrue slowly (and therefore get absorbed by the $\alpha$ terms) while the process of upskilling tends to occur alongside temporary reductions in paid work.[16] Importantly, the parameters in the variance equations often have the reverse signs to the mean equations, indicating that the same changes that lead to increases in income also point to reductions in risk. The most notable examples of this are the indicators of working habits (i.e. "Part Time", "Not Working" and "Work Hours") which are typically significant, and switch signs in five out six instances.

From the estimates in Table 1 we generate the insecurity measures given in EQ (3-4) and EQ (7-8). Before analyzing the results however, we briefly perform a validation exercise by showing that the measures (i) behave as expected in a variety of contexts and (ii) reproduce standard empirical results found in other papers. Given the widely established empirical links between insecurity and health (Staudigel, 2016) we take data on subjective self-assessments (recorded on five-point scales) and use fixed-effects models to show that the expected negative relationships hold. This analysis is repeated for life satisfaction scores (on five/ten-point scales) and again the anticipated negative relationship emerges, albeit less robustly in this case (Table 6 in the Appendix).[17]

To examine cross-national differences in income insecurity, Table 7 in the appendix presents raw estimates averaged by year. Immediately we see that US estimates are always substantially higher - a result which persists over all four measures. Across the pooled sample, the Dalton indices averaged around 0.012 in the US and 0.0022 in Germany, indicating that for log utility, about 1.2% and 0.22% of welfare derived from income is lost through unpredicted volatility. In this instance

[16] These coefficients will therefore not reflect the long-run benefits of education.

[17] The lack of statistical significance in some of these cases is likely due to the limited $T$ dimensions of our satisfaction data. Since the RDU measures are proportional to scale we condition on the log of income.

the greater average income in the US offers some protection relative to Germany, although as per Figure 1 this effect is relatively small.

Conversely if risk is considered in purely scale-invariant terms, the Atkinson indices imply that around 12% and 2.1% of income respectively could be sacrificed to eliminate risk. It is interesting to observe that when comparing across countries the ratio between the measures is fairly stable. Thus regardless of whether we prefer a scale invariant conceptualization of risk ($I^{AT}$) or one that considers both the level and the degree of variation ($I^{DN}$) the US has from four to five times the level of insecurity of Germany. The reference dependent measures tell a similar story. $I^{RD}$ averaged around 1.26 in the US and 0.32 in Germany, while the corresponding figures for $I^{EL}$ are 3.25 and 1.63. Therefore, the risk of negative year-to-year fluctuations, whether adjusting for baseline effects or not, is two to four times larger in the US.

We argue that these magnitudes are both large and meaningful for understanding recent trends in the global political and economic environment.[18] If economic insecurity is in fact a source of ill health and social malaise, then *ceteris paribus* we would expect to see more of these problems in countries where risk is higher. This finding may offer a partial explanation for the relative social unrest in the United States compared to Germany, and other related phenomena such as the differential trends in "deaths of despair" across the two countries (i.e. lifestyle related mortality from drugs, alcohol and suicide) outlined by Case and Deaton (2017). Similarly, if persons with secure economic futures are able to adopt more cosmopolitan ethical values than those who do not (Inglehart, 1977), then high and unevenly distributed risk may also be a source of cultural and political polarization, as found in the US (Gentzkow, 2016) but less pronounced in Germany (Barberá, 2015).

This finding of higher income risk in the United States is also surprising as there is a body of literature on income dynamics comparing these two countries, with the general result that German

[18] The Atkinson estimates can be placed in context by considering them relative to rates real per capita income growth. In the US, annual growth from 1993-2013 was approximately 1.3%, while the indices grew 3.9%, from 11.2 % to 14.1% over the same period. Thus the rise in insecurity (considered in more detail below) offsets approximately three years of economic progress. In Germany, there was no aggregate change in the Atkinson metric, while real per capita incomes grew at almost 1.5%.

incomes are more mobile than their US counterparts (e.g. Bayaz-Ozturk *et al.*, 2014; Burkhauser and Poupore, 1997). There are a couple of reasons why our results may be different. Firstly, as our measures are largely driven by unpredictable movements, they are quantifying subtly different phenomena to most mobility studies. If US incomes are more prone to intertemporal "flux" in the form of mean reverting volatility (Fields and Ok, 1996) or alternating short-term transitions (Anderson, 2018) this would (i) be reflected in increased values for our EUT risk measures, (ii) be consistent with higher values for the RDU measures, and (iii) do little to mitigate ingrained inequality, and hence explain all three stylized facts. Secondly Bayaz-Ozturk *et al.* (2014) who present a cross-national analysis similar to our own, exclude East German data from their analysis (which is included here) and which they argue substantially increases their estimates of German mobility.

Interestingly, a partial explanation for why the US estimates are so much higher is also buried in the coefficients in Table 1. All four measures are either heavily or entirely dependent upon the variance terms, which have similar non-constant components (given by $\mathbf{z}'_{it+1}\hat{\boldsymbol{\theta}}$), leaving the country-specific autonomous terms $\hat{\gamma}_{US}$ and $\hat{\gamma}_{GER}$ (which differ strongly) as the primary driver of cross-national differentials.[19] This implies that the main reasons US insecurity is higher is related to factors outside the model, which vary across countries, but not across individuals or over time. Although any invariant country-specific factors may account for this difference, the most plausible candidates are related to ingrained differences in the respective welfare states, labor laws and other socioeconomic institutions. An implication for policy is that making long-term progress in ameliorating economic insecurity may require addressing fundamental issues related to the role of governments and the provision of social insurance.

In order to assess trends Figure 2 (below) and Figure 3 (in the appendix) graph the time series.[20]

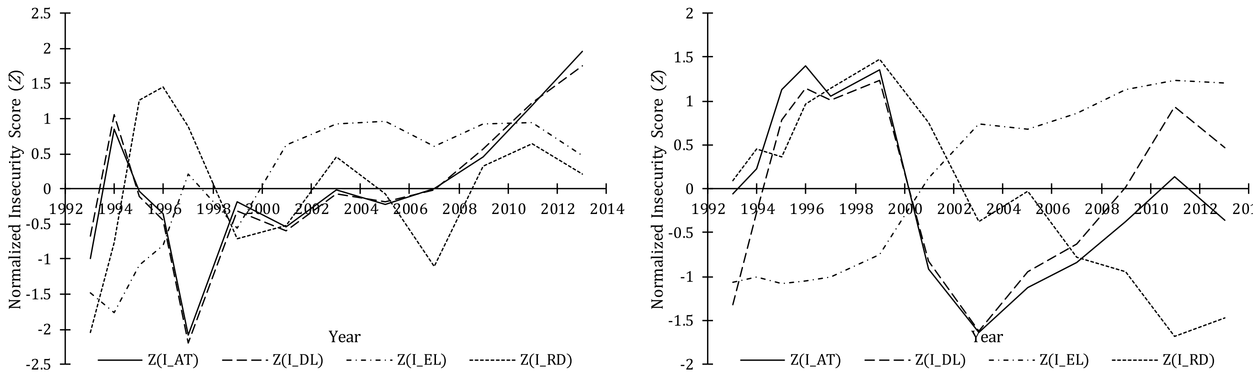
[19]Pooling the national panels shows that almost 85% on the variation in log predictive variance are explained solely by differences in these terms.

[20]We formalize this by regressing each annual average upon both a constant and time trend, and report the p-values on the latter to establish significance. For the US we obtain $I^{DN}$ (p=0.030), $I^{AT}$, (p=0.023) $I^{EL}$, (p=0.001) and $I^{RD}$ (p=0.013) and hence all indicators shows significant positive trends. For Germany we obtain $I^{DN}$ (p=0.070), $I^{AT}$, (p=0.072) $I^{EL}$, (p=0.000) and $I^{RD}$ (p=0.002). For three variables ($I^{DN}$, $I^{AT}$, $I^{RD}$ ) these slopes were negative while the strongest result is for $I^{EL}$ which had a positive slope.

The averaged levels are presented in Figure 3 while Figure 2 accounts for distributional differences by plotting $z$ transformations centered around zero. The normalized results for the US (left panel) are intuitive and are mostly consistent across the measures. The EUT measures followed each other closely, declining during the economic expansion in the mid-to-late 1990s before rising strongly from 1999 until 2013. The reference dependent measures also increased after 1999, although less steadily, peaking in 2011 before falling again in 2013. Given these patterns, it appears that the EUT indices more closely track anecdotal perceptions of insecurity. The fact that these grew sharply after 2008 while the reference dependent measures did not is notable. The financial crises and the deep slump that followed appeared to drive unpredictability in the level of income, but had only limited impacts upon reference dependent changes. As the former capture the types of risks more relevant for middle and lower income persons, this suggests that the contraction was likely to have had regressive distributional impacts on wellbeing.

Nonetheless, from the general upward tilt in all four measures it emerges that rising US insecurity is a stylized fact that is largely independent of the type of measure used. This observation also appears in works that have quantified *ex post* volatility using a range of income/earnings variables (e.g. Dynan *et al.*, 2007; Hacker, 2006; Shin and Solon, 2011; Ziliak *et al.*, 2011) over a similar period. It is also notable that while insecurity was especially high after the crisis years, the indices had been increasing for close to a decade earlier - aside from the short recession in 2001, income risk rose steadily during periods of relatively low unemployment and healthy output growth. The fact that insecurity could rise steadily while the economy operated at capacity suggests that cyclical features do not constitute a complete explanation for this phenomenon. Instead factors that operate over longer time horizons are needed to explain at least some aspects of these trends.

Figure 2: $Z$-Normalized Average Insecurity Estimates 1993-2013: - United States and Germany




Note: The left panel gives trends in all four normalized indices for the US from 1993-2013 while the right panel gives the equivalent trends for Germany. The raw (non-normalized) data are available in the appendix. *Z(I_AT)*, *Z(I_DL)*, *Z(I_RD)* and *Z(I_EL)* refer to indices defined in EQ (3-4) and EQ (7-8) respectively. Source: Authors' own calculations from CNEF data set.

Turning to the German data (right panel) we do not see a consistent trend emerging in the manner as for the US. The EUT and RDU indices again follow different trajectories, highlighting the fact that empirical results can be sensitive to alternative conceptual definitions. In this case the EUT measures reached their maximal values around 1996 and 1999, and fell to their respective minimums in 2003, with some signs of increase evident thereafter. These measures also hit a local peak in 2011, suggesting rising risk in the latter part of the decade when income risk is conceptualized in level-based terms. The $I^{EL}$ index followed a similar path, falling in 2001 and rising thereafter, while $I^{RD}$ was anomalous and fell throughout the decade. Notably, Germany did not experience a major economic contraction such as was seen in the US and other developed countries after 2008, and hence we did not anticipate seeing rising scores in the latter part of the period. Rather, the most relevant economic developments in Germany were likely the Hartz reforms (a set of major market-orientated labor market reforms) initiated in 2003. This ushered in a period of slightly rising insecurity thereafter, especially with respect to the level based indices. Nonetheless, in comparison to the US the estimates for Germany were fairly flat over time - only the trends in $I^{EL}$ are comparable in absolute terms.

**Trends in Covariates**

In order to better understand the drivers of rising insecurity, it is possible to decompose changes into contributions from developments in $\mathbf{x}'_{it}$ and $\mathbf{z}'_{it}$. Since the period of the clearest increase over both countries occurred from 2001-2013, we will use this window to examine the factors that account for our observed trends. While it would be possible to perform this decomposition over the full time-span of our data, focusing on this period is advantageous for several reasons. Firstly, as most papers cite increasing economic risk as typical, understanding the drivers of this phenomenon may have some broad international relevance. Secondly, to aid interpretation we standardize our estimates by the total degree of change, which becomes difficult when the denominator is close to zero. Thirdly, during our chosen window there was a fairly strong level of agreement on the trend in income insecurity, both across countries and across measurement concepts. The latter point is especially relevant as the decomposition we employ is only feasible for the level-based Dalton and Atkinson indices (analytical derivatives are needed), and therefore it is desirable to confine the analysis to a time when there is general consistency across the measures.

To proceed, we take 1st order Taylor series expansions of EQ (3) and EQ (4) such that each index may be approximated as a linear sum of its covariates. The partial derivatives are

$$\frac{\partial \hat{I}_{it}^{DN}}{\partial \hat{\mu}_{it+1}} = \frac{\hat{\alpha}_i + \mathbf{x}'_{it+1}\hat{\boldsymbol{\beta}}}{\left(\hat{\alpha}_i + \mathbf{x}'_{it+1}\hat{\boldsymbol{\beta}} + \frac{1}{2}\exp\left(\hat{\gamma} + \mathbf{z}'_{it+1}\hat{\boldsymbol{\theta}}\right)\right)^2} - \frac{1}{\hat{\alpha}_i + \mathbf{x}'_{it+1}\hat{\boldsymbol{\beta}} + \frac{1}{2}\exp\left(\hat{\gamma} + \mathbf{z}'_{it+1}\hat{\boldsymbol{\theta}}\right)} \tag{10}$$

$$\frac{\partial \hat{I}_{it}^{DN}}{\partial \hat{\sigma}_{it+1}^2} = \frac{\left(\hat{\alpha}_i + \mathbf{x}'_{it+1}\hat{\boldsymbol{\beta}}\right)\exp\left(\hat{\gamma} + \mathbf{z}'_{it+1}\hat{\boldsymbol{\theta}}\right)}{2\left(\left(\hat{\alpha}_i + \mathbf{x}'_{it+1}\hat{\boldsymbol{\beta}}\right) + \frac{1}{2}\exp\left(\hat{\gamma} + \mathbf{z}'_{it+1}\hat{\boldsymbol{\theta}}\right)\right)^2} \tag{11}$$

$$\frac{\partial \hat{I}_{it}^{AT}}{\partial \hat{\sigma}_{it+1}^2} = \frac{1}{2}\exp\left(\hat{\gamma} + \mathbf{z}'_{it+1}\hat{\boldsymbol{\theta}} - \frac{1}{2}\exp\left(\hat{\gamma} + \mathbf{z}'_{it+1}\hat{\boldsymbol{\theta}}\right)\right) \tag{12}$$

Defining $\mathbf{x}'_1$ and $\mathbf{x}'_2$ and $\mathbf{z}'_1$ and $\mathbf{z}'_2$ as averaged values of the predictors in time periods 1 and 2, we use the linear approximations to break down the contributions of each variable to the overall change.

$$\Delta \hat{I}^{DN} \cong \frac{\partial \hat{I}_{it}^{DN}}{\partial \hat{\mu}_{it+1}} \left(\mathbf{x}'_2 - \mathbf{x}'_1\right) \hat{\boldsymbol{\beta}} + \frac{\partial \hat{I}_{it}^{DN}}{\partial \hat{\sigma}_{it+1}^2} \left(\mathbf{z}'_2 - \mathbf{z}'_1\right) \hat{\boldsymbol{\theta}} \tag{13}$$

$$\Delta \hat{I}^{AT} \cong \frac{\partial \hat{I}_{it}^{AT}}{\partial \hat{\sigma}_{it+1}^2} \left(\mathbf{z}'_2 - \mathbf{z}'_1\right) \hat{\boldsymbol{\theta}} \tag{14}$$

Table 2: Decompositions of the Trend in EUT Measures: - US and Germany

| Variable | United States | | | Germany | | |
|---|---|---|---|---|---|---|
| | $\Delta x_{ij}$ | $\%\Delta I^{DN}$ | $\%\Delta I^{AT}$ | $\Delta x_{ij}$ | $\%\Delta I^{DN}$ | $\%\Delta I^{AT}$ |
| Education | 0.7420 | 5.26% | 4.47% | 0.3591 | 7.14% | 6.91% |
| Married | -0.0221 | 1.74% | 2.09% | -0.0228 | 3.92% | 3.39% |
| Divorced/Separated | -0.0005 | -0.12% | -0.01% | 0.0322 | -0.25% | -0.08% |
| Widowed | -0.0077 | -0.92% | -0.83% | 0.0019 | 0.16% | 0.15% |
| Household Head | 0.0323 | 8.09% | 5.16% | 0.0405 | 2.28% | 1.41% |
| Household Person | -0.1631 | 3.25% | 3.36% | 0.1604 | -13.26% | -11.60% |
| Children | -0.0188 | 0.58% | 1.05% | 0.0702 | -7.01% | -9.22% |
| Part Time Work | -0.0110 | -2.21% | -2.04% | 0.0408 | 7.79% | 7.06% |
| Not Working | 0.0520 | 30.72% | 30.43% | -0.0023 | -1.18% | -1.07% |
| Work Hours | -82.740 | -0.21% | -0.14% | -67.851 | 6.08% | 5.24% |
| Employment by State | -0.0495 | 25.25% | 24.21% | -0.1068 | -69.0% | -61.5% |
| Employment by Education | -0.0471 | -3.98% | -3.73% | -0.0730 | 27.84% | 24.74% |
| Income by State | -630.28 | 3.10% | 2.77% | -2334.2 | 23.23% | 19.22% |
| Trend | 10.000 | 21.03% | 24.85% | 10.000 | 129.1% | 130.9% |
| Age | 0.7425 | -13.80% | -13.73% | 1.7006 | -98.9% | -91.5% |
| Age Squared | 71.659 | 14.26% | 14.19% | 145.25 | 79.53% | 73.59% |
| Female | 0.0017 | 0.01% | 0.01% | 0.0575 | 2.60% | 2.40% |
| Nonwhite | 0.0459 | 7.94% | 7.90% | - | - | - |
| Total | | 100% | 100% | | 100% | 100% |

Note: Results represent decompositions of insecurity trends based upon averaged covariate vectors for 2001 and 2013. All estimates use linearized approximations to EQ (3) and EQ (4) and the results are standardized in terms of the total change in these indices. Results for the US are presented in the first three columns while results for Germany are in the last three.

Table 2 attributes the trends in these linearized indices to the covariates, where for clarity all contributions are standardized as a proportion of the total difference. For the US, the key results are in the second and third columns, where each value represents the proportion of the total increase in insecurity that would have been induced by a *ceteris paribus* change in that variable. For both the Dalton and Atkinson indices, the most notable contributors are (i) changes in employment conditions (either at the individual or aggregate level), (ii) household structure, (iii) the increasing share of the nonwhite population, and (iv) the passage of time captured by the trend variable. Combining the employment indicators implies that deteriorating labor market conditions account for approximately 50% of the rise in income insecurity. German results in columns 5 and 6 are somewhat different, where for both measures the incremental rise in insecurity is the end result of several factors pushing in opposing directions. As the total change is small (the denominator in our standardized estimates) the proportional changes are often large and occasionally exceed 100%. The most notable factor was the increased age of the German population - according to our model older individuals tend to be more secure, and hence the increase in average age offsets other factors, such as an evolving household structure. However, despite these changes, a general finding is that the passage of time (whether captured by the trend term or the age variables) is an important source underpinning changes in income insecurity. Such a result is largely uninformative however, as these variables are standing in for factors omitted from the model that (i) directly affect insecurity and (ii) that have increased over time. In the section below we consider two plausible explanations for this result.

**Policy Regimes**

A well-known argument advanced by Hacker (2006) is that market-orientated economic policy could be a driver of the trends outlined above. While there are theoretical arguments supporting such a link, it a challenge empirically to attribute changes in income risk to a particular type of policy. However, this hypothesis can be indirectly examined by linking variations in insecurity with an individual's local political environment. Since conservative governments are more likely to pursue market-based approaches, while liberal governments are more likely to fund social safety nets, systematic fluctuations in insecurity that appear after changes in governments provide a useful identifying mechanism.

To operationalize this idea, we compiled a data set of government identities, using dummy variables for each country differentiating between conservative (Republican - US / Christian Democratic Union - Germany) and liberal (Democratic - US / Social Democratic Party - Germany) state administrations as per the affiliation of the Governor/Minister-President each year.[21] The effects of liberal/conservative policy regimes on our measures are then assessed using regression models.

We account for endogeneity using a lagged regime dummy, and each insecurity score is regressed against a fixed effect and a time trend. As most of our data appear at two year intervals this is the time-frame we allow for any effects upon insecurity to materialize. We do not employ data on incomes, working hours or other individual-specific factors that were used to generate the measures in order to avoid simultaneity. Two specifications of our models are used. The first defines subgroups at the individual level (and hence uses individual fixed-effects) while the latter groups observations by state and therefore uses state dummies to control for group heterogeneity. In each case standard errors are clustered by the relevant grouping.

Table 3: Estimates of the Effect of Policy Regime Change on Risk Measures

| | United States | | | | Germany | | | |
|---|---|---|---|---|---|---|---|---|
| Risk Measure | $I^{DN}$ | $I^{AT}$ | $I^{EL}$ | $I^{RD}$ | $I^{DN}$ | $I^{AT}$ | $I^{EL}$ | $I^{RD}$ |
| $\Delta I$ | 8.6E-05** | 6.7E-04** | 2.5E-01** | 3.1E-03 | 8.8E-07 | 3.0E-05 | 4.6E-01*** | -1.1E-02* |
| Ave $I$ | 0.0122 | 0.1159 | 3.0534 | 1.2602 | 0.0022 | 0.0216 | 1.6570 | 0.3199 |
| $\%\Delta I$ | 0.70% | 0.58% | 8.19% | 0.25% | 0.04% | 0.14% | 27.94% | -3.38% |
| Individual FE | N | N | N | N | N | N | N | N |
| State FE | Y | Y | Y | Y | Y | Y | Y | Y |
| $\Delta I$ | 4.6E-05 | 4.1E-04 | 3.1E-01*** | 7.5E-03 | -6.2E-06 | -5.7E-05 | 3.0E-01*** | -1.2E-02* |
| Ave $I$ | 0.0122 | 0.1159 | 3.0534 | 1.2602 | 0.0022 | 0.0216 | 1.6570 | 0.3199 |
| $\%\Delta I$ | 0.38% | 0.35% | 10.15% | 0.60% | -0.29% | -0.27% | 18.23% | -3.78% |
| Individual FE | Y | Y | Y | Y | Y | Y | Y | Y |
| State FE | N | N | N | N | N | N | N | N |

Note: The table gives estimates of the effects of changes in government on the mean value of the insecurity indices by state. The left panel uses fixed effects at the individual level while the right panel uses state fixed effects. Standard errors are clustered accordingly. *, ** and *** denote significance at 10%, 5% and 1%.

[21] In instances when the state does not appoint a Governor (US) or Minister-President (Germany) (e.g. Berlin) we use the party identity of the mayor or other head of government instead. When administrations changed within a year the party in power for the longer time period was used, while if the ideology of the head of government is unclear (e.g. when they belong to third parties or were independent candidates) we attempt to match via voting records or ties to major parties.

Table 3 shows results on the correlation between political alignment and insecurity. The leftmost four columns in the first row give the estimated effect of a change from liberal to conservative government in the US controlling for state-specific effects. The second row gives the average score across all time periods, and as the effect sizes are generally small, the percentage change is also reported in the third row. The estimates show that when individual-specific factors are accounted for, a change from liberal to conservative government predicts slight increases in income insecurity over the next two years. This result holds for both EUT measures and the change based expected loss index (the estimate is positive but not significant for the reference dependent change measure). Comparable results in the lower panel also show positive impacts when controlling for individual-specific factors although the estimates are less likely to be significant. Taken together we infer that conservative government is weakly correlated with increases in income insecurity in the US, a finding which seems intuitive given the policy mix normally favored by conservative administrations. However it should be emphasized that the estimated effect sizes are extremely small - typically accounting for less than a percentage point change in the underlying indices. Thus political factors are probably a contributing factor, however they are of only limited use in explaining the variations in our data.

In Germany the results again do not conform to a simple narrative. Both reference dependent measures are significantly correlated with changes in administration (this holds for both state and individual fixed effects) but the signs on these measures are contradictory. Similarly the EUT measures also change signs, being positive but insignificant when state-specific factors are accounted for, and negative and insignificant when controlling for individual factors. We interpret this lack of significance/robustness as being consistent with the idea that the major political parties in Germany do not differ detectably in terms of their regulatory approach or management of social safety nets.

### Global Competition

A second factor which may explain rising risk exposure is the potential for increased international competition with low wage countries to make labor income (as a component of household income) more downwardly volatile. Various forms of this hypothesis exist (Milberg and Winkler, 2009; Scheve and Slaughter, 2004; Standing, 2008) and are particularly compelling in their capacity to explain the increases in insecurity believed to have occurred in most developed countries. Rising trade exposure has also been proposed as a source connecting economic insecurity with political polarization (Autor *et al.*, 2016), and upsurges in nationalism and nativist politics (Inglehart and Norris, 2016; Winlow *et al.*, 2017). Again it is hard to explicitly test this link, although we may gather some informal evidence by examining trends in our measures for various subsets of our data. If increasing international competition plays a significant role, we would expect greater upward trends in sectors that are more vulnerable to competition from low wage workers, and smaller trends for those in industries which are less threatened (assuming that trade exposure is also increasing with time). Table 4 presents such an analysis. We take manufacturing as an example of an industry that is fairly open to competition from the developing world, due to the tradability of its product, and the service sector as an example of an industry that is more insulated.[22]

Defining dummies $D_M$ and $D_S$ for these industries, fixed-effect models of the form

$$I_{it} = \alpha_i + \xi_t + \lambda_M t \times D_{Mit} + \lambda_S t \times D_{Sit} + \varepsilon_{it} \tag{15}$$

are estimated for each measure using OLS to identify the respective trends. This specification accounts for time-invariant differences in insecurity levels for persons across both industries, which may occur due to naturally varying levels of risk across the industrial divide, or due to one-time selectivity of workers into specific industries.

[22]Evidently such a dichotomy is imperfect and subject to spill-overs. E.g. a service worker operating in a manufacturing industry may still be affected by these types of trade exposure. Nonetheless, greater international competition across these sectors is only required to hold on average for our analysis. Other factors omitted from our model but changing over time, such as differing rates of industrial consolidation between manufacturing and services (which may also influence income risk) could also affect our results. There is some empirical evidence for this latter phenomenon, particularly in the US (e.g. Azar *et al.*, 2017; Azar *et al.*, 2018; Neumark *et al.*, 2008), although we note that such consolidation may occur *in response* to increasing competitive pressure from global trade.

Table 4: Trends in Risk Measures - Manufacturing and Service Industries: - US and Germany

| | United States | | | | Germany | | | |
|---|---|---|---|---|---|---|---|---|
| | $I^{DN}$ | $I^{AT}$ | $I^{EL}$ | $I^{RD}$ | $I^{DN}$ | $I^{AT}$ | $I^{EL}$ | $I^{RD}$ |
| $\hat{\lambda}_M$ | 5.02E-5*** | 5.84E-4*** | 2.61E-1*** | 2.16E-2*** | 2.23E-6 | 5.90E-5*** | 5.26E-2*** | 3.54E-3*** |
| $\hat{\lambda}_S$ | 2.64E-5*** | 3.98E-4*** | 2.43E-1*** | 1.77E-2*** | -1.15E-6 | 2.95E-5** | 5.70E-2*** | 6.49E-3*** |
| $\hat{\lambda}_M - \hat{\lambda}_S$ | 2.38E-5*** | 1.86E-4*** | 1.80E-2 | 3.90E-3** | 3.38E-6*** | 2.95E-5*** | -4.40E-3 | -2.95E-3*** |

Note: The first row provides the time trends for each index for individuals in the manufacturing industry while the second row contains the trends for individuals in the service industry. The last row gives the difference in risk trends for persons in manufacturing relative to services. *, ** and *** denote 10%, 5% and 1% significance respectively.

Estimates in Table 4 shed light on this trade exposure hypothesis. For the US there were upward trends for both manufacturing and service workers (first two rows), but in all four cases there were greater rates of increase for the manufacturing group. Tests on the differentials being equal to zero (third row) are rejected for $I^{DN}$, $I^{AT}$ and $I^{RD}$ and hence the finding holds across a broad range of insecurity concepts. In terms of proportions, the rates of increase for manufacturing ranged from only slightly higher than for services (107%) to almost double (190%). Compared to the population-wide trends in Figure 3 (which showed approximately 30% increases for the level-based metrics from 1993-2013) these differences are relatively small, equal to approximately 15% of the total increase over this time. Relative effect sizes are also greater for these EUT measures, which indicates that the trends we have observed are more likely to be meaningful for lower income individuals. In Germany, both level based indices also conform to this pattern, although the reference dependent indices do not. As the coefficients switch signs proportional differences are not reported, however in absolute terms the parameter estimates are much smaller for Germany. One plausible explanation is that the relatively skillful nature of the German manufacturing industry may provide some insulation against competition from low wage countries. Further, differences in corporate governance across countries may account for some of this phenomenon. For example, unlike in the US, German regulation requires the presence of labor representation on corporate boards (Du Plessis *et al.*, 2017) which is thought to incentivize quality, and therefore reward skill. Labor representation is also likely to promote longer-term worker wellbeing more generally, which may include enhancing job security. Such a finding is also consistent with both academic work and public opinion. For example Scheve and Slaughter (2001) show that hostile attitudes to trade and immigration policy are disproportionately held by people with poorer labor market prospect (who are also likely to face greater trade exposure) in the US, while Guiso *et al.* (2017) uncover similar results for Europe.

## 4 Conclusion

This paper makes two contributions towards the analysis of income insecurity, a concept which feeds into the broader phenomenon of economic insecurity. First, several econometric techniques were developed that capture stress-inducing micro-level income risk. Second, these techniques were used to study insecurity in the US and Germany, with the aim of identifying the underlying drivers economic anxiety in developed Western countries.

Our methodological contribution is built upon econometrically generated predictive densities for household incomes. Using panel data models, we derived two *ex ante* insecurity measures employing Expected Utility Theory that capture risks related to the *level* of household income. Further, as the concept of income insecurity has an implicit psychological component, we developed two reference dependent utility measures that focus on intertemporal *change*, which account for important features of Prospect Theory.

Applying these measures to harmonized panel data shows some stark differences between our two countries. For the US, the results conform quite closely to popular opinion. Firstly, income insecurity is much higher than in Germany, a fact that persists over a variety of conceptualizations of risk. As this appears to be mostly due to a larger constant term in its variance equation, any explanation must come from factors that differ across countries, but do not vary over individuals or time. As such, institutional factors such as differences in social safety nets, corporate governance and labor market regulation appear to be suitable candidates. Secondly, we showed that insecurity in the US rose fairly steadily since 2001. Using some decomposition techniques, we find that approximately 50% of this increase can be attributed to changes in labor market variables, such as declining employment rates and reductions in annual hours worked. Demographic factors such as changing household composition and an increasing non-white share of the population also contributed. We also considered two other possible explanations for this rise - an evolving political environment and an increase in the supply of low skilled labor, and found qualified evidence that both factors played a minor role.

Conversely, our findings for Germany do not adhere to a simple underlying narrative. Insecurity is low in Germany and relatively stable - we were not able to identify trends that were significant and robust to the choice of measure. Additionally, the balance of political power in Germany appears largely unrelated to insecurity, and in contrast with the US, there is only weak evidence that the phenomenon is connected to globalization. This is remarkable given the period contained major political upheaval in the aftermath of reunification, the introduction of extensive labor market reforms, a global economic contraction and a debt crisis.

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## Appendix

## Descriptive Statistics

Table 5: Descriptive Statistics: - Key Variables - Full Samples

| | United States | | | | Germany | | | |
|---|---|---|---|---|---|---|---|---|
| | Mean | Stdev | Min | Max | Mean | Stdev | Min | Max |
| Income | 36262 | 43353 | 0.546 | 4483646 | 27240 | 20078 | 7.553 | 1917081 |
| Education | 12.74 | 2.520 | 1 | 20 | 13.042 | 3.272 | 7 | 18 |
| Age | 40.76 | 16.591 | 6 | 103 | 41.93 | 12.18 | 17 | 91 |
| Female | 0.529 | 0.499 | 0 | 1 | 0.480 | 0.500 | 0 | 1 |
| Non White | 0.395 | 0.489 | 0 | 1 | - | - | - | - |
| Married | 0.533 | 0.499 | 0 | 1 | 0.638 | 0.480 | 0 | 1 |
| Single | 0.317 | 0.465 | 0 | 1 | 0.249 | 0.432 | 0 | 1 |
| Divorced/Separated | 0.111 | 0.314 | 0 | 1 | 0.097 | 0.295 | 0 | 1 |
| Widowed | 0.039 | 0.193 | 0 | 1 | 0.016 | 0.127 | 0 | 1 |
| Household Head | 0.529 | 0.499 | 0 | 1 | 0.573 | 0.495 | 0 | 1 |
| Household Person | 3.155 | 1.540 | 1 | 14 | 3.041 | 1.333 | 1 | 13 |
| Children | 1.004 | 1.225 | 0 | 11 | 0.776 | 1.028 | 0 | 10 |
| Full Time Work | 0.447 | 0.497 | 0 | 1 | 0.627 | 0.484 | 0 | 1 |
| Part Time Work | 0.268 | 0.443 | 0 | 1 | 0.359 | 0.480 | 0 | 1 |
| Not Working | 0.286 | 0.452 | 0 | 1 | 0.013 | 0.114 | 0 | 1 |
| Work Hours | 1368 | 1052 | 0 | 12635 | 18567 | 830.5 | 9 | 7445 |

Note: Estimates for the US are given in the leftmost columns and estimates for Germany are on the right. All calculations are based upon the pooled samples of 181567 observations (US) and 79272 (Germany). In each case the columns give means, standard deviations and minimum/maximum values respectively.

## Income Insecurity, Self-Rated Health and Life Satisfaction

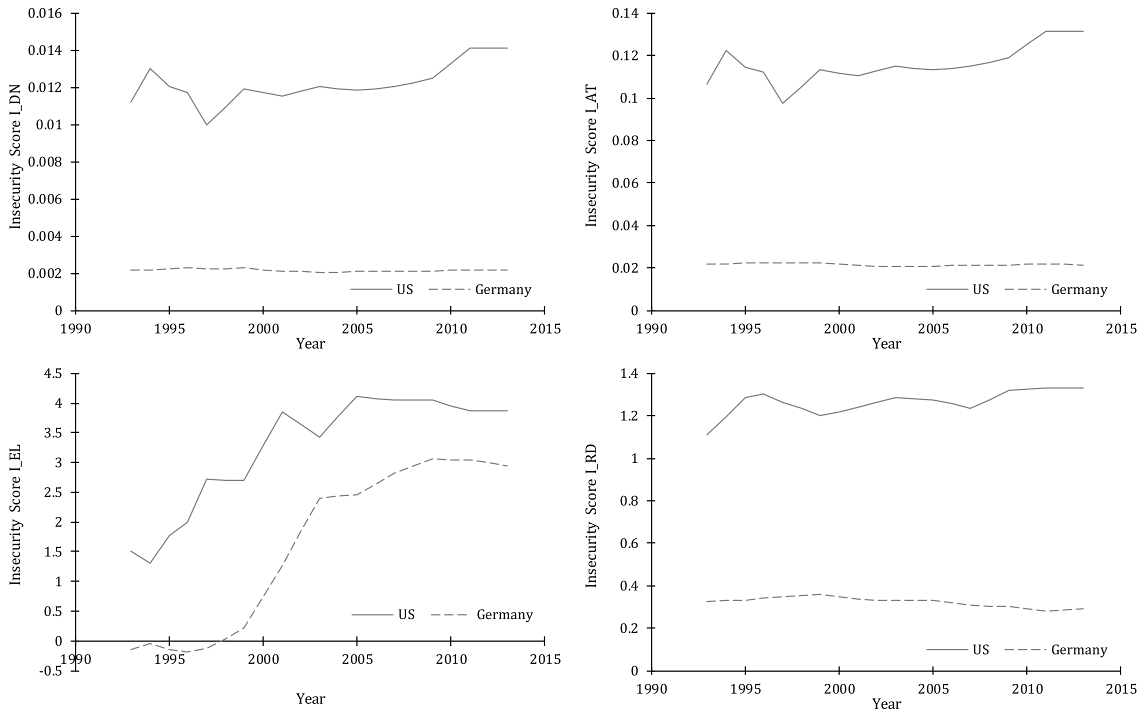
Table 6: Income Insecurity as a Correlate of Self-Rated Health and Life Satisfaction

| | United States | | | | Germany | | | |
|---|---|---|---|---|---|---|---|---|
| Variable | $I^{DL}$ | $I^{AT}$ | $I^{RD}$ | $I^{EL}$ | $I^{DL}$ | $I^{AT}$ | $I^{RD}$ | $I^{EL}$ |
| Health | -16.869*** | -2.1410*** | -0.0286*** | -0.0003* | -11.207 | -2.2964*** | -0.0300*** | 0.0034*** |
| Standardized $\beta$ | -0.2058*** | -0.2481*** | -0.0361*** | -0.0009* | -0.0243 | -0.0495*** | -0.0096*** | 0.0057*** |
| Life Satisfaction | -1.7319 | -0.2007 | 0.0006 | -0.0003 | -57.381*** | -7.1447*** | -0.0213 | 0.0039*** |
| Standardized $\beta$ | -0.0094 | -0.0089 | 0.0008 | -0.0037 | -0.0339*** | -0.0392*** | -0.0079 | 0.0228*** |

Note: The table gives results for fixed-effects regression models (i.e. $y_i = \alpha_i + \mathbf{x}_{it}^{'}\beta + \varepsilon_{it}$) where self-assessed health is the dependent variable and measures $I^{DL}$ $I^{AT}$ $I^{RD}$ and $I^{EL}$ along with log income are covariates. The first row gives parameter estimates and the second standardizes the coefficients using the standard deviation of each measure. Results for the US are on the left and Germany on the right. Health is measured in units from 1-5 while life satisfaction is 1-5 in the US and 1-10 in Germany. The standardized rows give each coefficient multiplied by the standard deviation of the respective measure. US estimates for life satisfaction scores are based upon a $T = 2$ panel which explains the lack of significance. Cluster robust inference is used and *, ** and *** denote significance at 10%, 5% and 1% levels respectively.

## Raw Trends in Insecurity Indices

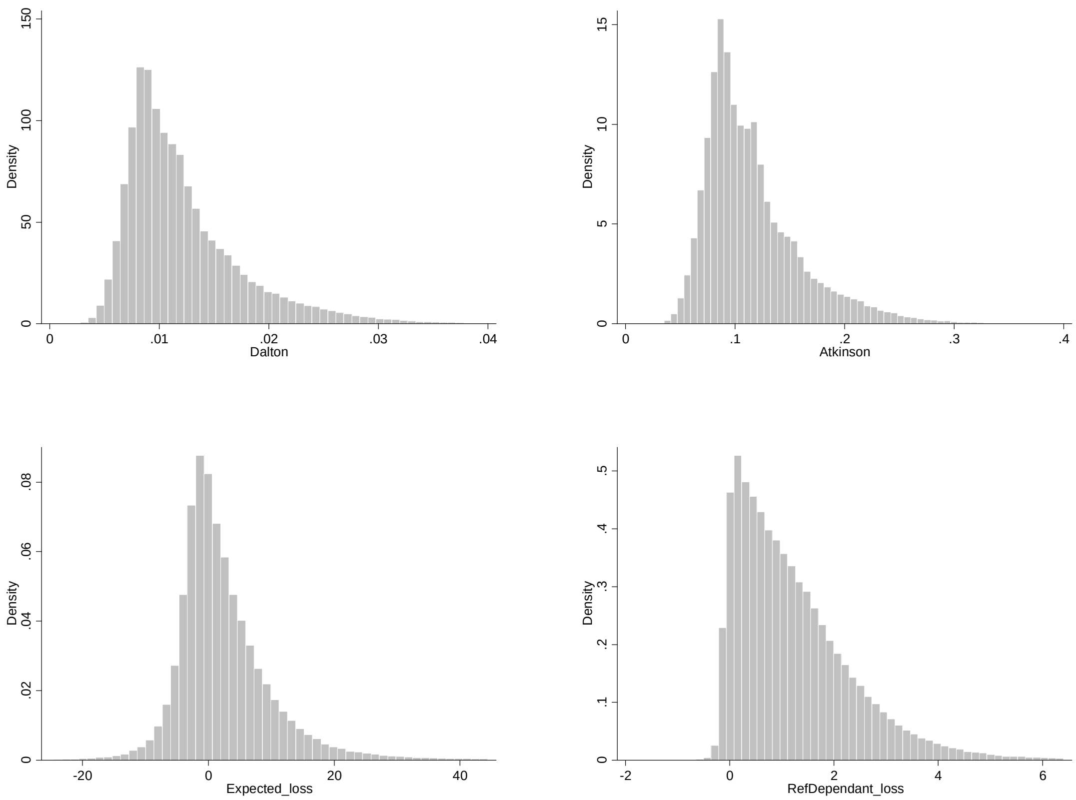
Figure 3: Insecurity Indices: Raw Trends: - US and Germany




Note: The solid lines depict results for the US while dashed lines give results for Germany. The top left panel shows the trend in Dalton indices (EQ 3) and the top right panel gives Atkinson indices (EQ 4). The lower left and right panels give trends in the expected loss (EQ 7) and reference dependent loss measures (EQ 8). Values for missing years are linearly interpolated.

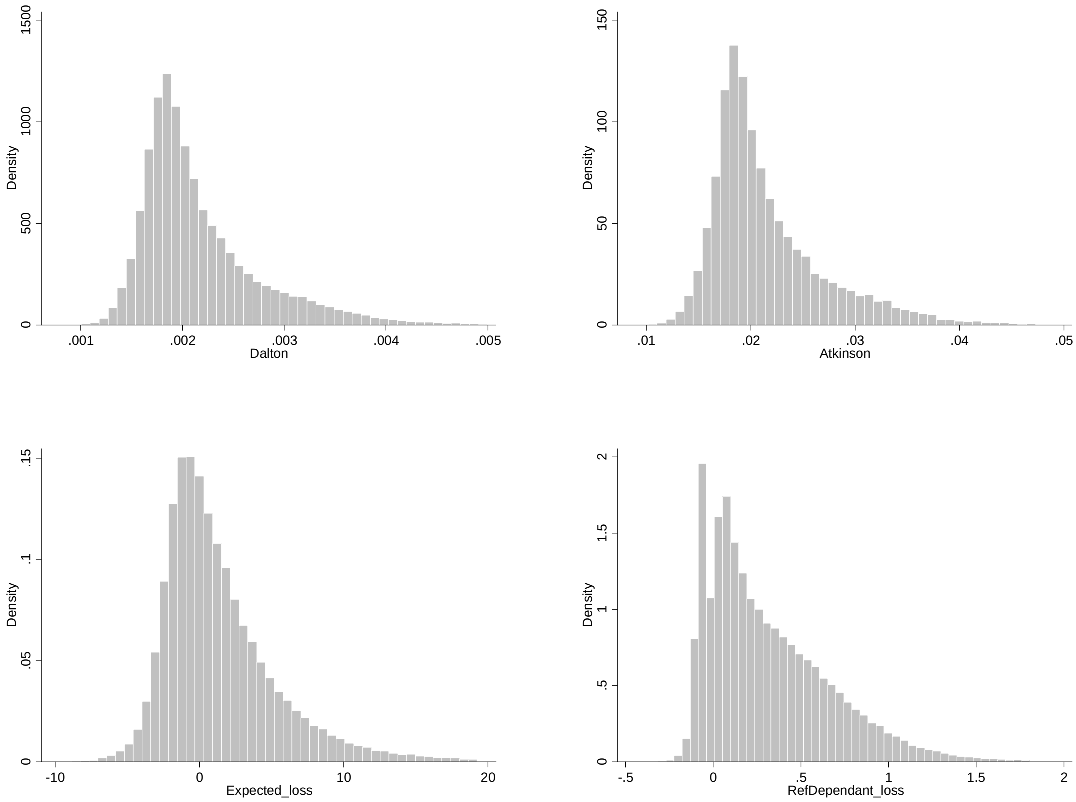
## Distributions of Insecurity Indices

Figure 4: Histograms of Insecurity Indices: - United States




Note: The top left panel shows the distribution of Dalton indices (EQ 3) and the top right panel gives the distribution of Atkinson indices (EQ 4). The lower panels show the distributions of the expected loss (EQ 7) and reference dependent loss measures (EQ 8). All estimates are based upon the pooled sample of 181567 observations.

Figure 5: Histograms of Insecurity Indices: - Germany




Note: The top left panel shows the distribution of Dalton indices (EQ 3) and the top right panel gives the distribution of Atkinson indices (EQ 4). The lower panels show the distributions of the expected loss (EQ 7) and reference dependent loss measures (EQ 8). All estimates are based upon the pooled sample of 79272 observations.

## Insecurity Estimates by Year

Table 7: Average Insecurity Estimates by Year: - US and Germany

| | United States | | | | Germany | | | |
|---|---|---|---|---|---|---|---|---|
| Year | $I^{DL}$ | $I^{AT}$ | $I^{RD}$ | $I^{EL}$ | $I^{DL}$ | $I^{AT}$ | $I^{RD}$ | $I^{EL}$ |
| 1993 | 0.0112 | 0.1065 | 1.1115 | 1.5017 | 0.0022 | 0.0216 | 0.3253 | -0.1541 |
| 1994 | 0.0130 | 0.1221 | 1.1957 | 1.3152 | 0.0022 | 0.0218 | 0.3292 | -0.0396 |
| 1995 | 0.0120 | 0.1147 | 1.2862 | 1.7656 | 0.0023 | 0.0224 | 0.3338 | -0.1502 |
| 1996 | 0.0117 | 0.1120 | 1.3001 | 2.0013 | 0.0023 | 0.0226 | 0.3405 | -0.1827 |
| 1997 | 0.0100 | 0.0973 | 1.2616 | 2.7116 | 0.0023 | 0.0223 | 0.3457 | -0.1241 |
| 1998 | 0.0110 | 0.1053 | 1.2319 | 2.7087 | 0.0023 | 0.0224 | 0.3512 | 0.0460 |
| 1999 | 0.0119 | 0.1134 | 1.2022 | 2.7059 | 0.0023 | 0.0225 | 0.3568 | 0.2161 |
| 2000 | 0.0117 | 0.1118 | 1.2200 | 3.2795 | 0.0022 | 0.0218 | 0.3463 | 0.7426 |
| 2001 | 0.0115 | 0.1103 | 1.2379 | 3.8531 | 0.0021 | 0.0211 | 0.3358 | 1.2692 |
| 2002 | 0.0118 | 0.1125 | 1.2614 | 3.6403 | 0.0021 | 0.0208 | 0.3334 | 1.8370 |
| 2003 | 0.0120 | 0.1147 | 1.2850 | 3.4275 | 0.0021 | 0.0206 | 0.3310 | 2.4047 |
| 2004 | 0.0119 | 0.1139 | 1.2807 | 3.7671 | 0.0021 | 0.0208 | 0.3319 | 2.4283 |
| 2005 | 0.0118 | 0.1130 | 1.2763 | 4.1067 | 0.0021 | 0.0209 | 0.3327 | 2.4518 |
| 2006 | 0.0119 | 0.1140 | 1.2554 | 4.0753 | 0.0021 | 0.0210 | 0.3206 | 2.6412 |
| 2007 | 0.0120 | 0.1149 | 1.2345 | 4.0439 | 0.0021 | 0.0211 | 0.3086 | 2.8305 |
| 2008 | 0.0123 | 0.1168 | 1.2768 | 4.0508 | 0.0021 | 0.0213 | 0.3053 | 2.9470 |
| 2009 | 0.0125 | 0.1187 | 1.3192 | 4.0576 | 0.0021 | 0.0214 | 0.3021 | 3.0636 |
| 2010 | 0.0129 | 0.1218 | 1.3249 | 3.8811 | 0.0022 | 0.0216 | 0.2912 | 3.0492 |
| 2011 | 0.0132 | 0.1249 | 1.3306 | 3.7047 | 0.0022 | 0.0217 | 0.2803 | 3.0348 |
| 2012 | 0.0137 | 0.1282 | 1.3312 | 3.7826 | 0.0022 | 0.0216 | 0.2852 | 2.9930 |
| 2013 | 0.0141 | 0.1315 | 1.3318 | 3.8605 | 0.0022 | 0.0214 | 0.2901 | 2.9511 |

Note: The table presents averaged insecurity measures by type, year and country. The first four columns give the EUT and RDU indices for the US while the latter four rows present equivalent estimates for Germany.