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Paper prepared for the 34th IARIW General Conference

Dresden, Germany, August 21-27, 2016

Session 4D: Well-Being II

Time: Tuesday, August 23, 2016 [Afternoon]

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June 26, 2016

Abstract

This paper develops a normative approach for measuring household-level income insecurity. We take panel data and employ fixed-effects models that allow for conditionally heteroskedastic error terms to generate predictive distributions for each individual's income in the coming year. From these predictive distributions we generate indices based upon expected utility (along the lines given by Ligon and Schechter (2003)), and alternative methods that employ reference-dependent functions that capture important features from Prospect Theory. Once established, the methods are applied to harmonized panel data from the US and Germany from 1993-2009. Our empirical analysis reveals much higher levels of household income risk in the US than in Germany, which can be mostly attributed to a higher level of unexplainable, time-invariant income volatility. Averaging across the sample reveals that US insecurity rose fairly steadily over time, while results for Germany are more ambiguous and depend upon the way that insecurity is defined. We examine potential drivers at the national level and find that changing macroeconomic conditions are unable to account for the observed trends in insecurity, while changing demographic factors (household sizes, racial composition and population age structure) appear to have some explanatory power for both countries. Increasing global competition and changes in economic policy are also identified as potential explanatory factors. Lastly the paper employs counterfactual estimation techniques to study variations in income insecurity *across* individuals. We isolate the impacts of an individual's labor market status and changes in household structure over time on the distribution of insecurity, and find that developments in the labor market since 2001 have disproportionately affected persons in lower income families. Conversely changes in household structure have also raised insecurity however the negative effects are fairly evenly distributed throughout the population.

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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 has brought long-lasting unemployment to many developed countries while less extensive social safety nets, lighter regulation of labor markets and changes in household structure have left people vulnerable to economic shocks. This increased vulnerability is likely to be impacting negatively upon individual wellbeing. Survey data shows that economic risks rank highly amongst the biggest worries that people face in life, while various hazards such as job insecurity or income volatility

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have been linked to a number of socioeconomic ills including diminished mental and physical health, increased rates of familial breakup, and other related factors such as suicide.¹

Given this pervasive array of consequences there is a need for economists to study risk as an individual or household-level concept. Spearheaded by works Osberg (1998), Hacker (2006), Western et al. (2012), Ligon and Schechter (2002), Calvo and Dercon (2005), Smith et al. (2009) and Bossert and D'Ambrosio (2013) (amongst others) there is now a growing literature that defines or quantifies some form of economic insecurity in developed and developing countries. Although there are many hazards that could plausibly make an individual insecure (such as an uncertain job or a lack of insurance) much of this literature has focused on income risk. Quantifying income risk in this manner is complicated however, as (i) not all income fluctuations are socially harmful, and (ii) the risks that are harmful are better characterized in terms of ex ante exposure rather than ex post volatility. However as differentiating between these concepts is not straightforward, and to date most empirical studies require the strong assumption that the latter acts as a suitable proxy for the former (e.g. Rohde et al., 2014).

The objectives of this paper are twofold. The first is to build upon the current techniques available to economists for studying household-level income risk. The methods employed are essentially adaptations of the theoretically appealing framework developed by Ligon and Schechter (2003). Like these authors, we employ panel data methods to forecast future distributions of household incomes and analyze the risk implicit in the predictive density. However we extend this technique in a number of important ways. Predictive densities for future incomes usually employ an assumption of homoskedasticity, implying that each individual has an identical residual variance. Since it has been well established that income volatility varies across individuals, and that this volatility is a primary driver of risk, it is necessary to look beyond constant variance assumptions when modeling individual-specific risk. Further if one is prepared to assume normality in the residual term in log-linear regressions, and if welfare is given by the log of income, then we are able to calculate measures of welfare loss due to risk exposure using simple closed-form expressions of parameters from our statistical models. As well as being convenient these equations make the functioning of the risk indices clear - it is simple to see how a change in mean income or a change in its variance will impact upon the result.

After establishing some conventional measures based upon Expected Utility Theory (EUT) we note that this method corresponds poorly with experimental evidence on risk preferences when the stakes are relatively small. Thus for developed countries where there is little chance of absolute destitution, economic risk as it is experienced is much better captured by the reference dependent methods employed in Prospect Theory (PT). By employing some of these reference dependent concepts we are able to develop additional insecurity measures that are more in line with psychological perceptions.

Secondly we apply these techniques empirically to study income risk and its distributions in the US and Germany since the early 1990s. These two countries make an especially interesting case study as they are both highly developed Western nations and hence reasonably comparable, however they differ substantively in terms of economic policy. The US is notable for its high income level but relatively small social safety nets and employee protection laws, while Germany has a lower average income, but lower inequality and a more extensive welfare state. To foreshadow our main findings we observe that despite a higher income level (which should ordinarily ameliorate risk), insecurity and risk are higher in the US than Germany. We trace this result primarily to a much higher level of autonomous variance in the predictability of log income, which suggests that the differences observed are mostly attributed to ingrained (invariant over time and over individuals) phenomena such as the institutional environments existing within the two countries. A number of further decompositions are used to identify the sources of changing insecurity over time.

Lastly, we also observe that regression based indices allow for some attractive decomposition methods for studying the effect of a particular covariate upon the distribution of insecurity, or its joint distribution with other variables such as income, age, education or household structure. There are a number of reasons why the distribution of economic risk may be of interest. For example insecurity may be considered especially problematic if it is highly

¹Papers that highlight the health consequences of economic insecurity include (but are by no means limited to) works by Catalano (1991), Ferrie (2001), Smith et al. (2009) and Rohde et al (2016), while studies Smock et al (2005) and Hardie and Lucas (2010) show that exposure to economic risks predict various measures of degradation in familial relationships. Similarly psychiatric research by Economou et al. (2013) seems to suggest that economic insecurity is the cause of increased suicide in Greece since the Eurozone crisis.

concentrated among certain individuals, especially if these persons share common some characteristic such as being relatively poor, having lower educational attainments or belonging to a particular racial group. Further it is likely that certain policy interventions will impact differently on different individuals, and hence to run simulations it is important to allow for these differential impacts. By using copula based methods along the lines designed by Roche (2012) it is possible to produce counterfactual densities such that the effect of a policy change can be simulated. This process can be used to gain insights into why insecurity differs across individuals, and how it may be ameliorated in especially at risk persons.

The paper is structured as follows. Section 2 derives the risk measures in terms of standard statistics obtainable from fixed effects models. Section 3 presents estimates of insecurity in our two countries and examines a number of plausible explanations for cross-national differences and trends in insecurity over time. Section 4 considers counterfactual approaches that may be used to understand the factors that generate insecurity while Section 5 summarizes and concludes. Supplementary material is presented in the appendix.

2 Modeling Income Insecurity in Panel Data

Our objective is to produce a model that captures the income risk that an individual faces at time t while thinking ahead about time $t + 1$. Since this future income is unknown, and may take on a range of possible values, it is important to consider the full distribution of possible values. Thus to model income insecurity we require the predictive distribution of future values based upon all relevant information up to time t . Panel data methods offer some considerable advantages over cross-sectional methods for obtaining predictive distributions. As well as possessing the required time-dimension, they have the ability to control for individual-level heterogeneity when modeling the response of income to external shocks. A logical starting place is the standard fixed-effects model frequently used in econometric analysis. This is given as

$$\ln(y_{it}) = \alpha_i + \mathbf{x}'_{it}\boldsymbol{\beta} + \varepsilon_{it} \quad (1)$$

where \mathbf{x}_{it} is a $k \times 1$ vector of determinants (one of which is a time trend), $\boldsymbol{\beta}$ a $k \times 1$ vector of parameters, α_i a time-invariant individual specific effect and ε_{it} an error term. We place ourselves in the shoes of an individual i at time t who has an income generating process given by this model. The income risk that this individual experiences is assumed to be a function of the distribution of outcomes that may be realized in period time $t + 1$ which may be obtained from EQ (1) via a simple forecast. If the error term can be assumed to be normal then for some future covariate vector \mathbf{x}'_{it+1} the predictive distribution for y_{it+1} will be lognormal. Thus for each individual we may use EQ (1) to obtain a future income distribution

$$y_{it+1} \sim \ln\mathcal{N}(\alpha_i + \mathbf{x}'_{it+1}\boldsymbol{\beta}, \sigma^2) \quad (2)$$

which provides a full characterization of the individual's exposure to income risk in the coming period.² One drawback of EQ (2) is that it is typically assumed that σ^2 is constant for both $i = 1, \dots, N$ and $t = 1, \dots, T$ and therefore the model implies a constant rate of income variance for all individuals in all time periods. Since this uncertainty is likely to be an important determinant of income insecurity the model is adapted to allow for differentials in volatility across both these dimensions. Thus we develop a Fixed-Effects Conditional Heteroskedasticity model

$$\ln(y_{it}) = \alpha_i + \mathbf{x}'_{it}\boldsymbol{\beta} + \varepsilon_{it} \quad \varepsilon_{it} \sim N(0, \sigma_{it}^2), \quad \sigma_{it}^2 = \exp(\gamma + \dot{\mathbf{x}}'_{it}\boldsymbol{\theta}) \quad (3)$$

Here our outcome is still of the log-linear functional form given in EQ (1) however the error variance is now parameterized such that it is made up of (i) the fixed component γ , and (ii) a component that varies across both time and individuals $\dot{\mathbf{x}}'_{it}\boldsymbol{\theta}$. The use of the exponential term ensures this term is always positive. There is also an important distinction between the covariate vector for the mean equation \mathbf{x}'_{it} and the variance equation $\dot{\mathbf{x}}'_{it}$.

²Sometimes the predictive variance also includes an adjustment for parameter uncertainty which we exclude for the sake of simplicity.

The former can only include time-varying factors due to the presence of the α terms while the latter can employ time-invariant regressors such as race, gender and age.

Models such as EQ (3) are advantaged in that they are able to distinguish between the types of income volatility that should and should not generate insecurity. Predictable fluctuations are typically not cited as drivers of insecurity (Western et al., 2012) as they can be planned for in advance, while unpredictable shocks will be drivers of insecurity as they represent the unknown risks to which an individual is exposed. In our model the former type of variation is captured by the parameters in the mean equation while the latter is contained in the variance equation. Therefore the choices of variables included in \mathbf{x}'_{it} and $\dot{\mathbf{x}}'_{it}$ effectively separate the concepts of raw income volatility from unpredictability that may be seen as a source of insecurity.

Estimating EQ (3) is more complicated than EQ (1) and requires a specialized maximum likelihood approach to handle the non-constant variance. To simplify the estimation we employ within transformations to eliminate the individual specific effect α_i and proceed via maximum likelihood employing our assumption of error normality. The log-likelihood function is

$$\ln \mathcal{L}(\beta, \theta, \gamma) = -\frac{nT}{2} \ln(2\pi) - \frac{1}{2} \sum_{i=1}^n \sum_{t=1}^T \left(\gamma + \mathbf{x}'_{it} \theta \right) - \frac{1}{2} \sum_{i=1}^n \sum_{t=1}^T \frac{\left(\ln(y_{it}) - \mathbf{x}'_{it} \beta \right)^2}{\exp(\gamma + \dot{\mathbf{x}}'_{it} \theta)} \quad (4)$$

and the model is fitted using the Newton-Raphson algorithm. Once estimated the individual-specific terms are recovered using $\hat{\alpha}_i = \bar{y}_i - \bar{\mathbf{x}}'_i \beta$ and predictive densities are generated for the coming year by combining the one-step-ahead covariate vectors \mathbf{x}'_{it+1} and $\dot{\mathbf{x}}'_{it+1}$ with our parameter estimates. Choosing appropriate values for these vectors represents a well established challenge in forecasting as it is likely that other variables will change besides the time dimension. However we use a standard simplifying assumption in the forecasting literature and only update the time dimension(s) (Tashman et al., 2000).³ Once we have an estimate for $f(y_{it+1})$ there are a number of ways to summarize the risk, and in particular the downside risk, in this distribution.

Methods Based Upon Expected Utility

A standard economic approach to modeling risk comes from the application of Expected Utility Theory (EUT) to a distribution of outcomes. In our context this involves specifying a welfare function $U(y)$ (where $U(y) \geq 0$, $U'(y) > 0$ and $U''(y) < 0$) and comparing the welfare in the predictive distribution with that of a degenerate distribution with the same mean. Related method has been employed in this context before, most notably by Ligon and Schester (2003) and Feigenbaum and Li (2011). Let us define $E[U(y_{it+1})]$ as the expected utility of income in 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. Using these values we may measure the loss in welfare using the following

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

Both these measures have parallels with the inequality literature. Here $I^{DN} \in [0, 1]$ corresponds to Dalton's (1920) index for the loss in welfare due to unequal distribution, while $I^{AT} \in [0, 1]$ is analogous to the Atkinson (1970) inequality metric. Both measures are equal to zero if the predictive distribution is degenerate, and via Jensen's Inequality, will take on strictly positive values when the variance is non-zero. A neat advantage of the log-linear framework we employ in EQ (3) is that if one is prepared to accept that $U(y) = \ln(y)$, then both measures have simple closed-form expressions in terms of the parameters from our Fixed-Effects regressions

$$I_{it}^{DN} = 1 - \frac{\hat{\alpha}_i + \mathbf{x}'_{it+1} \hat{\beta}}{\hat{\alpha}_i + \mathbf{x}'_{it+1} \hat{\beta} + \frac{1}{2} \exp(\hat{\gamma} + \dot{\mathbf{x}}'_{it+1} \hat{\theta})} \quad (5)$$

³This problem may be circumvented by specifying the model using lagged regressors however the fact that the US data has missing waves after 1997 makes this approach unfeasible.

$$I_{it}^{AT} = 1 - \exp \left(-\frac{1}{2} \exp \left(\hat{\gamma} + \mathbf{x}'_{it+1} \hat{\boldsymbol{\theta}} \right) \right) \quad (6)$$

The neat expressions in EQ (5-6) allow the relative impacts of the mean and variance of log income to become apparent. In the case of I^{DN} the index is increasing in the variability of income $\exp \left(\hat{\gamma} + \mathbf{x}'_{it+1} \hat{\boldsymbol{\theta}} \right)$ and decreasing in the level (both the individual specific effect α_i and the time-varying component $\mathbf{x}'_{it+1} \hat{\boldsymbol{\beta}}$). Both these characteristics make sense if insecurity is related to the threat of future destitution. Conversely I^{AT} is simply an increasing function of the forecast variance, and therefore insecurity is simply a downside-risk weighted function of the unpredictability of future incomes. The index is homogeneous of degree zero in y indicating that a richer individual can experience just as much of a relative decline in welfare as a poorer person. Given these differing sensitivities to the level of income, I^{DN} and I^{AT} characterize risks related to absolute shortfalls and relative volatility respectively.

Measures Based on Reference Dependent Utility

Although the expected utility model employed above represents a theoretically appealing method for quantifying risk, there is a large volume of literature showing that its predictions correspond poorly with experimental data on preferences (Barbaris, 2012). For example in developed countries (where absolute material deprivation is rare) psychological responses to risk are sensitive to changes in incomes rather than the levels. Furthermore the standard assumption of concavity of welfare in income holds for gains but breaks down for losses, implying a *diminishing sensitivity* to more extreme outcomes, or alternatively, a preference for the status quo. And individuals 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.

Rather than relying on the EUT framework, key insights from Prospect Theory can be incorporated into our analysis using Reference Dependent Utility (RDU) functions (Maggi, 2004). Suppose that each individual has some benchmark income level to which they have habituated against which losses and gains are defined. Utility is then an S-shaped function of the discrepancy between the observed income level and the reference level, where the specific utility function captures both loss aversion and diminishing sensitivity. Let us define an individual's current income as their reference point such that the variable $\tilde{y}_{it} = y_{it+1} - y_{it}$ captures deviations from this baseline. A standard reference-dependent parametric functional form is

$$v(\tilde{y}) = \begin{cases} \tilde{y}^\xi & \tilde{y} \geq 0 \\ \lambda(-\tilde{y})^\xi & \tilde{y} < 0 \end{cases} \quad (7)$$

where $\xi < 1$ and $\lambda < -1$ govern the risk preferences. Parameter ξ controls the degree of concavity/convexity for gains/losses while λ gives the loss aversion. Tversky and Kahneman (1992) provide 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 that losses are more than twice as potent as gains. Using this framework the expected utility relative to the baseline is

$$V(\tilde{y}) = \int_{-y_{it}}^0 \lambda(-\tilde{y})^\xi f(\tilde{y}) d\tilde{y} + \int_0^\infty \tilde{y}^\xi f(\tilde{y}) d\tilde{y} \quad (8)$$

Two specific measures of insecurity are built upon this concept. The first is relatively straightforward and is simply the negative of $V(\tilde{y})$, giving the expected loss in welfare in the coming period. The second measure assumes that the individual is forward looking and actively anticipates a change in income from her current level. This measure assesses the expected utility in EQ (8) against the utility experienced if the individual receives exactly her forecast income in the coming period, given by $v(\hat{y}_{it+1} - y_{it})$. 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 income in the coming year. The two measures are therefore

$$I_{it}^{EL} = -V(\tilde{y}_{it}) \quad (9)$$

$$I_{it}^{RD} = v(\hat{y}_{it+1} - y_{it}) - V(\tilde{y}_{it}) \quad (10)$$

Unlike the indices given in EQ (5) and EQ (6), the reference dependent utility loss in EQ (9-10) can take on both negative and positive values. If the distribution $f(\tilde{y})$ has a large degree of downside risk (typified by high probabilities for negative values) then 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 $f(\tilde{y})$ describes a distribution of mostly positive values then the individual is likely to experience a gain, and hence should be regarded as having low (negative) insecurity.

Since the measures obtained from PT are concerned with changes rather than levels these indices must be applied and interpreted differently to the EUT measures. The notion of reference dependent utility is only appropriate when the level is unimportant, and therefore these measures are only suitable for analyzing high income countries. To illustrate, consider two individuals where one is rich and the other is in danger of absolute poverty. If both are at risk of losing a fixed sum such as \$1,000 they will have *ceteris paribus* identical values for I^{EL} and I^{RD} , however the poorer individual's risk exposure is likely to be much more stressful. Conversely if neither is likely to experience an absolute material shortfall and income losses simply represent painful adjustments from subjective equilibria then these measures will perform as expected. Lastly to distinguish between I^{EL} and I^{RD} we emphasize that the former is sensitive to predictable change while the latter only captures unpredictable change. If the forecast distribution for y_{it+1} is degenerate but has a different mean to y_{it} then I^{EL} will take on some non-zero value, indicating the utility experienced while moving between two known income levels. Conversely I^{RD} removes the effect of anticipated change such that only unpredictable income movements are considered. Thus if predictable fluctuations (such as due to a change in household structure or a decline in working hours) are considered to be harmful then the naive measure is appropriate, while if we are only interested in unpredictable changes then I^{RD} should be used.

3 Income Insecurity in the US and Germany

Once we have established the basic measures we now present an empirical application modeling the distribution of economic risk in the US and Germany. The central focus of the analysis will be directed towards developing a deeper understanding of (i) why the levels are so different across these two countries, (ii) why insecurity levels have changed over time, and (iii) the factors explaining interpersonal differences within each country.

Our data come from the Cross-National Equivalence File which is a collection of harmonized panels from a number of developed countries. We employ the longest possible panel that is consistent across both countries which runs from 1992 to 2009.⁴ Since US data omit every second year from 1997 onward these waves are excluded for Germany as well to maintain comparability. Thus we end up with 11 waves for each country spanning 17 years. The length of the panel is crucial in the analysis for consistent estimation of individual specific effects.

The main variable of interest is household post-government income which is the sum of inflows less taxes for all household members, standardized using the Buhmann et al. (1988) $\theta = 0.5$ equivalence scale. We use real income throughout and employ PPP exchange rates such that observations for both the US and Germany are measured in 2009 US Dollars. Our set of covariates is limited by (i) our choice to employ harmonized panels that have less extensive sets of controls, and (ii) by our focus on fixed effects models which cannot estimate the effects of race, gender, age or other background characteristics (parental income and education levels, place of birth etc) that would typically be of interest. Nonetheless the ability for these models to handle all time-invariant heterogeneity

⁴Data before 1992 is omitted for Germany due to the reunification of the East and West in 1990.

represents a considerable advantage over other specifications. Observations on education level, household size and composition, marital status, employment status and working hours are used as individual-specific predictors of income fluctuations. We also employ some aggregate covariates to capture macroeconomic factors. These include employment rates by regional area and education level and estimates of average income by state.

The models are fitted to both 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. Inference is based upon cluster robust covariance estimation and degree-of-freedom adjustments are made to account for the initial estimation of individual-specific effects $\alpha_i \dots \alpha_n$.

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

		US		Germany	
Variable Type	Variable Name	Mean	Log Variance	Mean	Log Variance
Individual/Household	Constant	10.380***	-1.203***	9.735***	-3.964***
	Education	-0.033***	0.018***	-0.008**	0.039***
	Married	0.146***	-0.289***	0.134***	-0.264***
	Separated/Divorced	0.083***	-0.062***	0.065**	0.080**
	Widowed	0.088***	0.191***	0.201***	-0.008
	Household Head	-0.542***	0.316***	-0.235***	0.321***
	Household Size	-0.031***	-0.043***	0.089***	-0.071***
	Children	-0.062***	-0.098***	-0.518***	-0.193***
	Part Time Work	-0.147***	0.197***	-0.044***	0.266***
	Not Working	-0.434***	0.831***	-0.124***	0.371***
	Work Hours	5.4E-05***	-6.2E-05***	7.9E-05***	-6.1E-05***
	Trend	0.271***	-0.246***	0.009***	0.002
	Employment Rate (S)	0.051**	0.012*	-0.730***	1.903***
	Employment Rate (E)	8.5E-06***	-1.1E-05	0.224***	0.365***
Aggregate	PC Output (S)	0.011***	0.005***	1.6E-05***	1.0E-05***
	Age		-0.020***		-0.037***
	Age Squared		2.5E-04***		2.9E-04***
	Female		0.011		0.151***
	Non-White		0.356***		
Fixed					
Supplemental	No. Groups	27619		23732	
	No. Observations	149342		100249	
	Log likelihood	-96379		3699	
	Pseudo R^2	0.599		0.692	
	D	9074		3973	

Note: The table provides parameter estimates for EQ (3) for US and German harmonized panel data 1993-2009. The dependent variable is the log of equalized household income and 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.

A preliminary glance at Table 1 reveals that 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 around 0.60 and 0.69 respectively. We test for the presence of conditionally dependent heteroskedasticity using the likelihood ratio

$$D = -2 \ln \mathcal{L}(\beta, \gamma) + 2 \ln \mathcal{L}(\beta, \theta, \gamma) \quad (11)$$

where $D \sim \chi^2_{k-1}$ under the null model captures 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 18.37 and hence we conclude that uneven variances are an important feature of the data.

Turning to the parameter estimates we see that the coefficients are generally in line with expectations, and are consistent across countries. In the income equations, married individuals engaged in full time employment in richer

states with higher output levels had larger incomes. The negative coefficients on educational attainment in the income equations are also expected as the process of upskilling is likely to occur alongside a temporary reduction in paid work. The coefficients in the variance equation tend to have the reverse signs to the income equation, indicating that the same changes that lead to increased income also point to a reduction in risk. The most notable examples of this are the indicators of working habits (labor market status and work hours) and household size, all of which lead to reductions in variance. The dummy for being the head of a household is notable as it essentially stands in for an indicator of a single person dwelling as all individuals within a household have the same income. These individuals have slightly lower incomes and higher predictive variances, likely in part to a lack of risk pooling available to persons in larger households.

From the estimates in Table 1 we generate the insecurity measures given in EQ (5-6) and EQ (9-10). Table 2 in the appendix presents the raw estimates averaged by year. Immediately we see that US estimates are almost always substantially higher over all four measures. The Dalton indices for the US average around 0.01 while for Germany the scores are around 0.003, indicating that about 1% and 0.3% of welfare derived from income is lost through uncertainty. The Atkinson indices are higher (on average about 0.1 for the US and 0.03 for Germany) however it is worth noting 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 around three times the level of insecurity of Germany. The reference dependent measures tell a similar story. In the US and Germany I^{RD} averages around 2.9 and 0.8 respectively while I^{EL} averages 1.15 and 0.26 across the two countries, a result which appears consistent with the EUT measures. However we do observe that when measuring insecurity in terms of raw reference dependent fluctuations (I^{RD}) Germany had slightly higher average levels in the late 2000s.

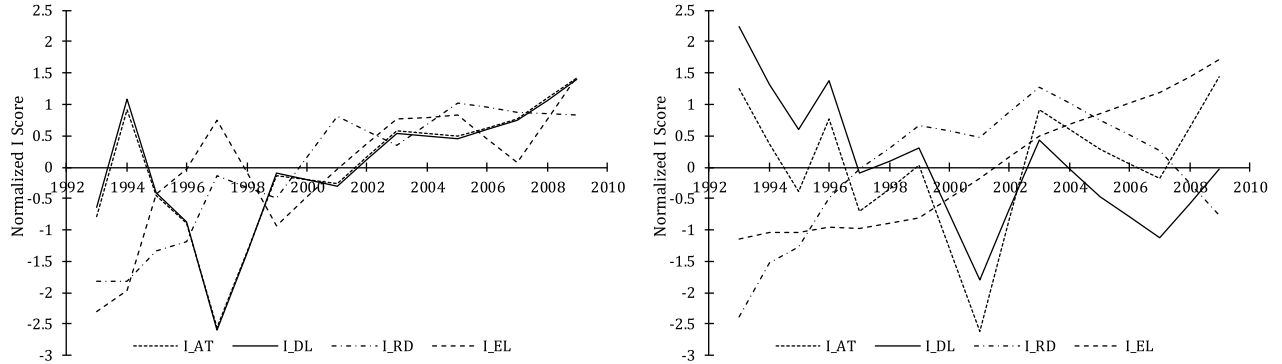
This finding of mostly higher income risk in the United States is somewhat surprising as there is a large body of literature on income dynamics that compares these two countries, with the general finding that German incomes are more mobile than their US counterparts (Bayaz-Ozturk et al., 2014; Burkhauser and Poupore, 1997). There are a few reasons why our results may be different. Firstly as our measures are capturing unpredictable movements in future incomes they are quantifying a subtly different phenomena to most mobility studies, which normally focus on the capacity of income movements to offset long run inequality. If US incomes are more prone to interpersonal 'flux' (in the form of short term mean reverting volatility) this would be reflected in increased values for our risk measures but would do little to mitigate ingrained inequality. 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 relative to the US. Thirdly these authors report that the mobility gap between these countries has been narrowing over time, and hence estimates based upon more recent data are expected to give higher values for the US than reported for previous periods.

An explanation for why income insecurity is so much higher in the US is buried in the coefficients in Table 1. Although the measures are dependent upon the full distribution of predictive incomes, it is the variance term that exerts the most influence. Further, the non-constant terms given by $\hat{\mathbf{x}}'_{it+1}\hat{\boldsymbol{\theta}}$ generally similar across the two countries, which leaves the country-specific autonomous components $\hat{\gamma}$ (which differ sharply) as the primary driver of the cross-national differential in risk. This implies that the main reasons why US insecurity is higher is related to factors that are fixed in both countries, both over individuals and over time. The result is interesting as it is strikingly consistent with the idea that differences in the respective welfare states, labor laws and other socioeconomic institutions that account for the relatively high US scores.

In order to assess trends Figure 1 graphs the time series. To account for the different distributional characteristics of the measures the plots homogenize each series using z transformations. The results are intuitive and are mostly (albeit not always) consistent across the measures. In the US, both the EUT measures declined in the earlier part of the period (from 1993 to 1997) before rising strongly to peak in 2009, while the reference dependent measures increased steadily throughout. Therefore rising US insecurity after 1997 appears as a stylized fact that is not dependent upon the form of risk being measured. This finding of increased income insecurity is consistent with a number of works, most notably Hacker et al (2010) who calculate trends in income risk as a share of the population classified as insecure, and Dynan et al (2007) who measure income volatility at the household level. Notably this rise in insecurity occurred mostly over a time of low unemployment and strong economic growth, which suggests

that cyclical factors are not a suitable explanation. Nonetheless the measures do peak in 2009, which is likely to be at least partially a result of the economic contraction occurring at the time. One important observation however is that our data for each year refer to incomes earned in the previous 12 months, and therefore the 2009 estimates are only capturing the early stages of the recession and crisis of 2008.

Figure 1: Average Insecurity Estimates 1993-2009 United States and Germany



Note: The left panel gives trends in all four normalized indices for the US from 1993-2009 while the right panel gives the equivalent trends for Germany. The raw (non-normalized) data are available in the appendix. Source: Authors' own calculations from CNEF data set.

Turning to the German EUT indices we also see insecurity declining in the earlier half of the period before increasing, however in this case the decline was longer lived, giving a distinct 'v' shaped trend bottoming out in 2001. It is worth noting that the steady rise in these measures after this point coincides roughly with the introduction of the Hartz reforms, which were a collection of market orientated labor and social welfare policies introduced in 2003. As a goal of these policies was to promote labor market flexibility it seems intuitive that they may increase insecurity, however the evidence in favor of this hypothesis is mixed. Indeed unlike the EUT indices, the reference dependent measures continued to increase steadily in Germany with no noticeable acceleration after the early 2000s. This apparent contradiction is consistent with a process where the predictive variance of Germany incomes was declining but income growth was also falling short of forecasts. Given that there is some disagreement between the measures it is clear that in order to establish a time trend in income insecurity one must specify whether it is the level or the change in income that is most relevant.

Trends in Covariates

In order to better understand the drivers of changing insecurity levels it is possible to decompose two of the indices into contributions from \mathbf{x}'_{it} and $\dot{\mathbf{x}}'_{it}$ as they evolve over time. Since the period of the clearest increase over both countries occurred from 2001-2009 we will use this window to examine the factors that most strongly accounted for its rise. Focusing on this period is advantageous as (i) most papers that examine similar issues cite rising income risk as a norm, and hence understanding the factors that underpin it may have some broad relevance, and (ii) during this time there was a fairly strong level of agreement on the trend in income insecurity both across countries and across the different types of measures employed. The latter point is especially relevant as the decomposition we employ is only feasible for the level-based Dalton and Atkinson indices and 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 approximations to EQ (5) and EQ (6) such that each index may be written as a linear sum of its covariates. The partial derivatives are

$$\frac{\partial \hat{I}_{it}^{DN}}{\partial \hat{\mu}_{it+1}} = \frac{\hat{\alpha}_i + \mathbf{x}'_{it+1} \hat{\beta}}{\left(\hat{\alpha}_i + \mathbf{x}'_{it+1} \hat{\beta} + \frac{1}{2} \exp \left(\hat{\gamma} + \hat{\mathbf{x}}'_{it+1} \hat{\theta} \right) \right)^2} - \frac{1}{\hat{\alpha}_i + \mathbf{x}'_{it+1} \hat{\beta} + \frac{1}{2} \exp \left(\hat{\gamma} + \hat{\mathbf{x}}'_{it+1} \hat{\theta} \right)} \quad (12)$$

$$\frac{\partial \hat{I}_{it}^{DN}}{\partial \hat{\sigma}_{it+1}^2} = \frac{\left(\hat{\alpha}_i + \mathbf{x}'_{it+1} \hat{\beta} \right) \exp \left(\hat{\gamma} + \hat{\mathbf{x}}'_{it+1} \hat{\theta} \right)}{2 \left(\left(\hat{\alpha}_i + \mathbf{x}'_{it+1} \hat{\beta} \right) + \frac{1}{2} \exp \left(\hat{\gamma} + \hat{\mathbf{x}}'_{it+1} \hat{\theta} \right) \right)^2} \quad (13)$$

$$\frac{\partial \hat{I}_{it}^{AT}}{\partial \hat{\sigma}_{it+1}^2} = \frac{1}{2} \exp \left(\hat{\gamma} + \hat{\mathbf{x}}'_{it+1} \hat{\theta} - \frac{1}{2} \exp \left(\hat{\gamma} + \hat{\mathbf{x}}'_{it+1} \hat{\theta} \right) \right) \quad (14)$$

Defining \mathbf{x}'_1 and \mathbf{x}'_2 as averaged values of the predictors at time periods 1 and 2 respectively we can use the following linear approximations to break down the contributions of each variable to the overall change. The results are presented in Table 2.

$$\Delta \hat{I}^{DN} \cong \frac{\partial \hat{I}_{it}^{DN}}{\partial \hat{\mu}_{it+1}} \left(\mathbf{x}'_2 - \mathbf{x}'_1 \right) \hat{\beta} + \frac{\partial \hat{I}_{it}^{DN}}{\partial \hat{\sigma}_{it+1}^2} \left(\hat{\mathbf{x}}'_2 - \hat{\mathbf{x}}'_1 \right) \hat{\theta} \quad (15)$$

$$\Delta \hat{I}^{AT} \cong \frac{\partial \hat{I}_{it}^{AT}}{\partial \hat{\sigma}_{it+1}^2} \left(\hat{\mathbf{x}}'_2 - \hat{\mathbf{x}}'_1 \right) \hat{\theta} \quad (16)$$

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

Variable	United States			Germany		
	Δx_{ij}	I^{DN}	I^{AT}	Δx_{ij}	I^{DN}	I^{AT}
Education	0.442	10.50	8.40	0.882	59.36	44.71
Married	-0.017	5.73	5.19	-0.014	6.51	4.75
Divorced/Separated	0.002	-0.13	-0.11	0.017	2.12	1.77
Widowed	-0.007	-1.34	-1.35	0.004	-0.17	-0.04
Household Head	0.031	12.62	10.35	0.052	30.17	21.60
Household Person	-0.186	8.50	8.41	-0.240	32.39	22.14
Children	-0.025	2.15	2.54	-0.033	7.87	8.23
Part Time Work	0.031	7.13	6.40	0.008	3.81	2.88
Not Working	-0.012	-11.76	-10.74	0.002	1.40	1.04
Work Hours	-62.43	4.77	4.07	-7.527	0.87	0.59
Employment State	0.001	-0.39	-0.33	-0.030	-100.82	-74.53
Employment Education	-0.004	-0.03	-0.05	-0.002	-1.30	-1.06
Income by State	-725.9	9.11	8.06	6701	99.36	90.27
Trend	8	39.44	46.07	8	18.82	23.99
Age	0.206	-4.60	-4.39	3.982	-249.94	-191.81
Age Squared	17.514	4.89	4.66	392.2	190.40	146.12
Female	0.001	0.01	0.01	-0.003	-0.84	-0.64
Nonwhite	0.034	13.40	12.78	-	-	-
Total		100%	100%		100%	100%

Note: Results represent decompositions of insecurity trends based upon averaged covariate vectors for 2001 and 2009. 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 variables in the models, where for clarity all contributions are standardized as a percentage 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 parabis* change in that variable. For both the Dalton and Atkinson indices the three most notable contributors are therefore (i) changes in household structure with a trend towards smaller units, (ii) the increasing share of the nonwhite populations, and (iii) the passage of time captured by the trend variable. Notably variables capturing labor conditions (labor market status, hours worked and employment rates by state and educational bracket) had very small contributions, implying that these changes were not primary drivers of the increase in US insecurity. German results in columns 5 and 6 are somewhat different, where for both measures the incremental rise in insecurity can be traced to a number of factors, some of which had substantial positive impacts and others substantially negative. 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 in our panel offsets other factors such as changing household structure and the linear trend variable.

A general finding from Table 2 therefore is that the passage of time (whether captured by the trend term or the age variables) seems to be a primary factor underpinning changes in income insecurity. Such a result is largely uninformative however as these variables are standing in for the factors omitted from the model that (i) truly affect insecurity and (ii) that change over time. In the section below we consider two further plausible explanations for this result.

Policy Regimes

An argument advanced by Hacker (2006) is that the secular rise of market friendly economic policy could be an important factor contributing to rising income insecurity. This idea can be examined in detail by drilling down into the smaller variations in the policy environment that occur within countries. That is, while it is hard to precisely attribute changes in income risk to any particular type of policy, we can look to link insecurity more broadly with variations in an individual’s local political environment. Fortunately changes in government at the state level provide an excellent mechanism for assessing the impact of competing economic models on risk. If Hacker’s (2006) thesis is correct then we would expect our measures to rise in states that switch from liberal to conservative governments (or vice versa). Thus the effect of policy regimes can be modeled by compiling a data set of state government identities to estimate the impacts on risk. To operationalize this we take the US data⁵ and create a dummy variable differentiating between more conservative and market friendly (Republican) and liberal (Democratic) states as per the affiliation of the governor each year.⁶

The effect of liberal/conservative policy regimes are then assessed using simple difference-in-differences type models. Each insecurity score is regressed against a fixed effect, a time trend and a regime dummy lagged by one year to circumvent endogeneity. This restricts the sample to the annual set of waves in the first half of our sample period. We do not employ data on incomes, working hours or other individual-specific data 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.

⁵German data are too limited for this exercise.

⁶When administrations changed within a year the party in power for the longer time period was used, while if the ideology of the governor is unclear (e.g. when they belong to third parties or are independent candidates) we attempt to match via voting records or ties to major parties.

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

Risk Measure	Individual Fixed Effects				State Fixed Effects			
	I^{DN}	I^{AT}	I^{EL}	I^{RD}	I^{DN}	I^{AT}	I^{EL}	I^{RD}
ΔI	0.00018***	0.00138***	0.00525	0.01624*	0.00013**	0.00102**	-0.11208	-0.00180
Ave I	0.0120	0.1103	1.6067	0.8381	0.0120	0.1103	1.6067	0.8381
% ΔI	1.51%	1.25%	0.32%	1.93%	1.12%	0.92%	-6.97%	-0.21%

Note: The table gives differences-in-differences 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%.

Table 2 shows some interesting results on the effect of political alignment on insecurity. The first row gives the estimated treatment effect of a change from liberal to conservative policy environment. When the EUT measures are employed we see significant increases in risk following such a change, a result that persists for both the individual and state based models. However for the RDU measures there is little sign that policy has any effect. Switching to conservative government yields a marginally significant increase in unpredicted reference dependent utility loss when individual fixed effects are used. However for the other specifications there is no significance and the coefficients are sometimes negative, implying a reduction in risk under conservative government.

Again the relationship between policy environment and income risk appears nuanced. More market friendly governments appear to increase risk when it is measured in terms of variation in the level, however there is no effect when measured in terms of reference dependent change. Further it is worth noting that even when significant, the coefficients in Table 2 are quite small. Switching to a conservative policy regime only increases the risk measures by 1-1.5%, or around 6% of an across-individuals standard deviation. Thus political factors are probably an important contributing factor, however they are mostly unable to explain the rise in reference dependent risk illustrated in Figure 1, and are of only limited use in explaining the rise in the EUT measures. It is plausible that these effects may aggregate over time and that the true impact of differing policy regimes is larger than reported, however this hypothesis requires a much longer data set than we have and hence it remains unexplored.

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. This hypothesis, as advanced by Scheve and Slaughter (2004) and Standing (2008) is particularly compelling as it has the capacity to explain the increases in insecurity that is believed to have occurred in most developed countries. Although it is hard to explicitly test this idea we may gather some indirect evidence by examining trends in our measures for various subsets of our data. If international competition plays a significant role in explaining increasing risk we would expect greater upward trends for persons employed in sectors that are most open to competition from low wage workers, and smaller trends for those in industries which are typically less threatened. Table 3 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 its reliance upon less skilled labor, and we take the service sector as an exemplar of an industry that is fairly insulated from this phenomenon. Models $I_{it} = \delta_M D_M + \delta_S D_S + \lambda_M t \times D_M + \lambda_S t \times D_S + \varepsilon_{it}$ (where D_M and D_S are dummies defining industries) are estimated for each measure using OLS to show trends for persons employed in these sectors for both the US and Germany.

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

	United States				Germany			
	I^{DN}	I^{AT}	I^{EL}	I^{RD}	I^{DN}	I^{AT}	I^{EL}	I^{RD}
Manufacturing	3.15E-05	3.45E-04	2.16E-01	1.50E-02	-9.14E-06	-3.28E-06	4.39E-01	-9.46E-03
Services	2.62E-05	2.37E-04	1.53E-01	3.61E-04	-1.08E-05	-1.66E-05	5.21E-01	-7.73E-03
$(\hat{\lambda}_M - \hat{\lambda}_S) / \hat{\lambda}_S$	0.202***	0.456***	0.408***	40.579***	-0.154***	-0.802***	-0.158***	0.224***

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 proportional increase in each index for persons in manufacturing relative to services. *, ** and *** denote 10%, 5% and 1% significance respectively.

Estimates show that for the US the rate of increase in insecurity was significantly greater for manufacturing than for services, a result that appeared uniformly across all four measures. This would appear to lend support for the idea that the supply of low wage labor from developing countries was a contributing factor to increasing income insecurity. However when we turn to results from Germany this anticipated pattern fails to emerge. Only the second reference dependent measure shows a sharper trend for persons in manufacturing while the other three indices all give greater rates of increase (or smaller rates of decline) for services. Taken at face value the German results seem at odds with both the US results and our hypothesis, however there are a number of other factors which can be used to reconcile these apparently divergent findings. Firstly if German manufacturing specializes in high quality goods (as is commonly perceived) then this would require a sophisticated skill base which may offer some insulation from global competition. Secondly, greater degrees of unionization for Germany manufacturing workers relative to their US counterparts would also be expected to provide some protection. Thirdly Germany's tax and redistribution system is notably more progressive than the US (Joumard et al., 2012). Thus increasing unpredictability in low-end pre-government income will translate more directly into insecurity as captured by our measures in the US than in Germany, which may also explain why German manufacturers are relatively unaffected by increasing global trade.

4 Decomposition Approaches

Having investigated some of the factors that underpin trends in insecurity at the national level we now consider changes that affect the distributions of our measures within countries. While it may be desirable to summarize income risk using a measure of central tendency such as the average of all individual-level estimates, it is also important to consider the way it is distributed with other variables such as income, age, education and gender. Furthermore for the purpose of policy making there is a need to understand how changing determinants may affect these joint distributions, as it is likely that policy makers are more concerned when income insecurity is concentrated in disadvantaged subsets of the population.

To investigate how the distribution of our risk measures may be affected by changes in the distributions of our covariates, we employ regression based decompositions along the lines developed (for the mean) by Oaxaca (1973) and Blinder (1973). There is an increasing focus on this type of analysis in microeconomic research (e.g. DiNardo, 1996; Autor, 2005; Bourguignon et al. 2008) with the aim of constructing counterfactual densities of a variable of interest subject to some policy intervention or other hypothetical scenario of interest. To illustrate we consider two populations P and Q with generic insecurity scores I , determined as

$$I^P = f(\hat{\alpha}^P, \hat{\beta}^P, \hat{\gamma}^P, \hat{\theta}^P; X_{t+1}^P) \quad \text{and} \quad I^Q = f(\hat{\alpha}^Q, \hat{\beta}^Q, \hat{\gamma}^Q, \hat{\theta}^Q; X_{t+1}^Q)$$

A counterfactual may be obtained by importing the distribution of some key input from population Q into population P . This involves replacing some column(s) in X_{t+1}^P with those from X_{t+1}^Q to give some hypothetical covariate matrix \tilde{X}_{t+1}^P . The counterfactual generic insecurity scores \tilde{I}^P are recalculated based upon the existing values for $\hat{\alpha}^P, \hat{\beta}^P, \hat{\gamma}^P, \hat{\theta}^P$ and the distribution is compared with that of I^P . This allows us to answer questions like “how would the distribution of insecurity scores change in P if variable j was distributed as it is in Q ?” By running these

simulations we can gain some insights into how various policy actions may affect the insecurity scores of different population subgroups. This type of analysis is clearly dependent upon the exogeneity of \mathbf{X}_{t+1} , which is a much more reasonable assumption when using panel data methods than in standard cross-sectional applications.

Importing the distribution for \mathbf{x}_{jt+1}^Q for \mathbf{x}_{jt+1}^P while (i) holding the other covariates constant, and (ii) retaining an appropriate covariance structure in X_{t+1}^P is an involved process. There are a several methods that may be used for this purpose including reweighting methods (Elder et al., 2015), decompositions using the Recentered Influence Function (RIF) (Firpo, 2007) and empirical copula based methods developed by Roche (2012). We use an empirical copula method designed to retain dependence using a concept of rank invariance while allowing us to impose any distributional form for our marginals. The method is especially neat when the data are continuous but requires some approximate methods when discrete covariates are used.

To begin we consider an example where X_{t+1}^P and X_{t+1}^Q contain only continuous variables and each is $n \times k$. We wish to model the distribution of insecurity scores if \mathbf{x}_{jt+1}^P was distributed in the same manner as \mathbf{x}_{jt+1}^Q . The probability integral transform $R_j = \hat{F}(\mathbf{x}_{jt+1}^P)$ for $j = 1, \dots, k$ removes the characteristics of each variable, leaving R_1, R_2, \dots, R_k where each $R_j \sim \text{Unif}[0, 1]$. The empirical copula $C : [0, 1]^k \rightarrow [0, 1]$ is then the joint distribution of the ranks which captures the dependence structure between the dimensions. The objective is to hold $C(R_1, R_2, \dots, R_k)$ constant while manipulating specific columns in X_{t+1} such that the distribution of \mathbf{x}_{jt+1}^P matches \mathbf{x}_{jt+1}^Q . This can be accomplished by employing the reverse transformation $\mathbf{x}_{jt+1}^P = F_{jP}^{-1}(R_j)$. The key point is that $F_{jP}^{-1}(R_j)$ may be imposed at will such that different distributional assumptions on a variable of interest can be modeled. Thus we develop the counterfactual covariate matrix for P importing j from Q

$$\tilde{X}_{t+1}^P = \left[F_{1P}^{-1}(R_1^P) \ F_{2P}^{-1}(R_2^P) \dots F_{jQ}^{-1}(R_j^P) \dots F_{kP}^{-1}(R_k^P) \right] \quad (17)$$

simply by replacing $F_{jP}^{-1}(R_j^P)$ with $F_{jQ}^{-1}(R_j^P)$. When the variables are discrete the process is not so simple and an approximate method is employed. Again we wish to simulate the effect of \mathbf{x}_{jt+1}^P taking on the distribution of \mathbf{x}_{jt+1}^Q and both vectors are $n \times 1$, but in this instance they only take on discrete values and as such we are unable to uniquely define the ranks R_j^P and R_j^Q . Such a situation may occur, for example, if j represents years of education, where all the observations take on a relatively small number of integer values. We order \mathbf{x}_{jt+1}^P and \mathbf{x}_{jt+1}^Q (non-uniquely) from $i = 1, \dots, n$ and partition each into $r = 1, \dots, s$ subgroups where each element within the subgroup takes on the discrete value x_{jr} . Elements in first partition of \mathbf{x}_j^P are indexed $i = 1, \dots, n_1^P$, the second partition $i = n_1^P + 1, n_1^P + 2, \dots, n_2^P$ etc with frequencies $n_1^P, n_2^P, \dots, n_s^P$ and $n_1^Q, n_2^Q, \dots, n_s^Q$. These may be represented as

$$\mathbf{x}_j^P = \begin{bmatrix} \mathbf{x}_{1j}^P \\ \mathbf{x}_{2j}^P \\ \vdots \\ \mathbf{x}_{sj}^P \end{bmatrix} \quad \mathbf{x}_j^Q = \begin{bmatrix} \mathbf{x}_{1j}^Q \\ \mathbf{x}_{2j}^Q \\ \vdots \\ \mathbf{x}_{sj}^Q \end{bmatrix}$$

By averaging the values in \mathbf{x}_j^Q over the subgroups defined according to \mathbf{x}_j^P we can calculate the approximate

$$\tilde{x}_r^Q = \frac{1}{n_r^P} \sum_{i=n_{r-1}^P}^{n_r^P} \mathbf{x}_{ij}^Q \quad r = 1, \dots, s$$

and use this to replace each element x_r^P . Thus we obtain the new vector $\tilde{\mathbf{x}}_j^Q$ which (i) has the exact same set of ranks as \mathbf{x}_j^P and the approximate distributional features of \mathbf{x}_j^Q . If $n_r^P = n_r^Q$ for $r = 1, \dots, s$ then the marginals of \mathbf{x}_j^Q and $\tilde{\mathbf{x}}_j^Q$ will be identical, while small departures in the frequencies will yield slight differences in distribution.

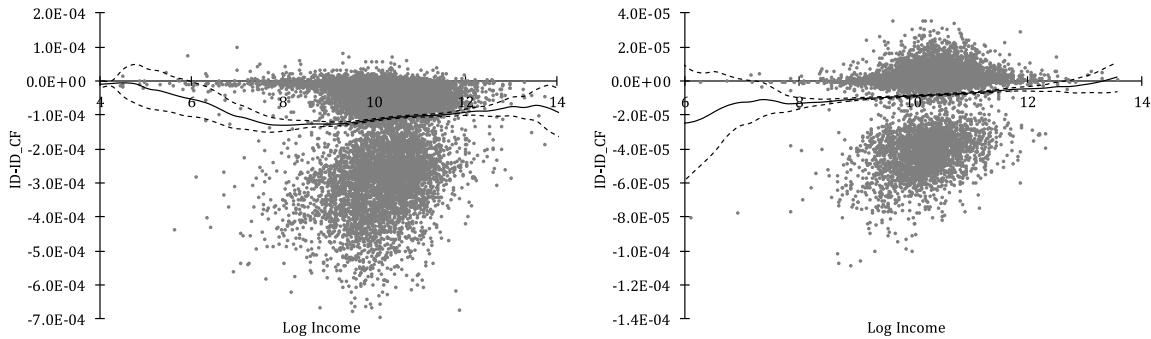
We conduct two counterfactual simulations using the Dalton measure given in EQ (5), while results based upon other indices are available from the authors upon request. We persist with this measure as it resembles most closely

the approach employed by other authors (e.g. Ligon and Schechter, 2003) and has the feature of being sensitive to both the level of income and its variance, which we regard as desirable.

The first simulation examines the effect that a changing labor market has on the distribution of our measure. Again we take two time periods (2001 and 2009) and consider both the increase in part time work, and the reduction in average working hours over this period that occurred in both countries. The idea here is that an increasingly casual workforce with reduced or unreliable working hours is likely to negatively affect persons who are primarily reliant upon this form of income to meet day-to-day expenses. As this group disproportionately consists of younger and lower income individuals, women, immigrants and the less well educated (Standing, 2011) it is worth testing to see if these changes have actually had their anticipated effects.

To gain an impression of how these developments impacted upon interpersonal differences we perform the rank based imputation method for these variables simultaneously. We then contrast the original estimates for 2009 with the counterfactuals obtained under this scenario. Figure 2 shows scatter plots of the difference in each estimate against logged income, while Table 5 gives averages of these differences across different population subsets.

Figure 2: Insecurity Differentials from Decreased Work Hours and Increased Part Time Work

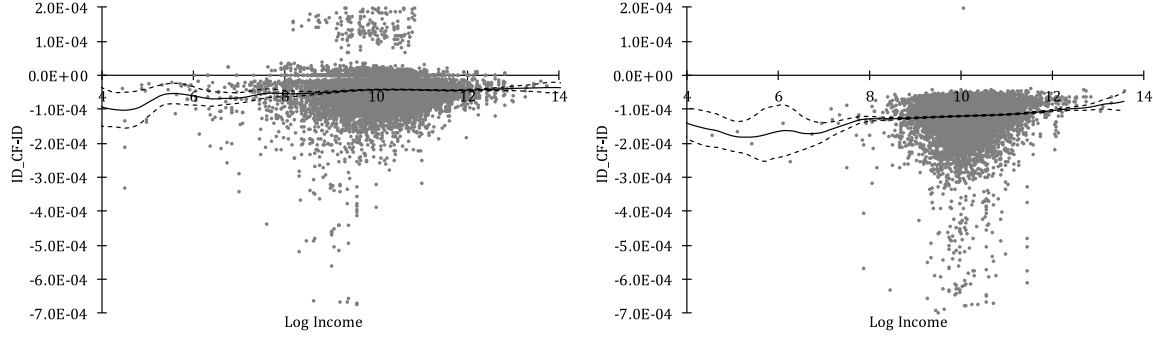


Note: The left panel shows the relationship between the change in insecurity due to the simulation and the log of income for the US. The right panel gives the equivalent result for Germany. Kernel regressions with 99% confidence intervals are also provided.

For the US (left panel) we see that most individuals would have slightly lower insecurity scores (i.e. negative changes) if it were not for distributional change in these labor market covariates. There is considerable heterogeneity in the responses ranging from slight positive changes to strong negative decreases, indicating that some individuals benefited from these distributional changes, although most did not. A kernel regression against logged income reveals that the largest negative impact at the lower end of the income distribution, which makes sense as these individuals are more likely to be reliant on casual labor income than the population as a whole. For Germany the results are similar, although the quantitative impact is substantially smaller. Again we see that the impact seems to diminish with rising incomes, and the mean effect becomes insignificantly different from zero at high levels.

Our second simulation considers the effect of diminishing household sizes over time. As noted above, shrinking households make individuals more insecure as there is less scope for informal insurance via risk pooling. Figure 3 shows that the changes in insecurity due to this trend were typically, although not uniformly negative for the US, while for Germany the impact appears to have been solely negative. However compared to the simulations for labor conditions the effect sizes are quantitatively small, implying that these demographic shifts are less responsible for differentials in insecurity than labor market changes. Interestingly again this effect appears to diminish slightly with income in both countries,

Figure 3: Insecurity Differentials from Changes in Household Size



Note: The left panel shows the relationship between the change in insecurity due to the simulation and the log of income for the US. The right panel gives the equivalent result for Germany. Kernel regressions with 99% confidence intervals are also provided.

In order to obtain a broader picture of the way that distributional changes in our covariates have impacted upon insecurity, we present some stratified averages of the measure below in Table 5.

Table 5: Averaged Dalton Indices by Population Subgroup

Variable		US			Germany		
		Observed	Sim 1	Sim 2	Observed	Sim 1	Sim 2
Education	Less than 12 Years	0.01370	0.01361	0.01365	0.00288	0.00287	0.00275
	12 Years	0.01232	0.01220	0.01227	0.00273	0.00272	0.00261
	More than 12 Years	0.01081	0.01070	0.01077	0.00266	0.00265	0.00255
Marital status	Unmarried	0.01196	0.01184	0.01192	0.00337	0.00335	0.00322
	Married	0.01055	0.01045	0.01051	0.00246	0.00245	0.00234
	Divorced/Separated	0.01393	0.01379	0.01388	0.00288	0.00287	0.00277
	Widowed	0.02205	0.02196	0.02198	0.00296	0.00296	0.00287
Income	1st Quartile	0.01490	0.01477	0.01485	0.00313	0.00312	0.00300
	2nd Quartile	0.01205	0.01194	0.01201	0.00280	0.00279	0.00267
	3rd Quartile	0.01064	0.01053	0.01059	0.00266	0.00265	0.00254
	4th Quartile	0.00981	0.00970	0.00976	0.00240	0.00240	0.00230
Age	Less than 30 Years	0.01106	0.01094	0.01102	0.00380	0.00378	0.00362
	30-60 Years	0.01093	0.01082	0.01089	0.00258	0.00257	0.00246
	More than 60 Years	0.01696	0.01687	0.01689	0.00254	0.00254	0.00245
Gender	Male	0.01140	0.01130	0.01136	0.00251	0.00250	0.00240
	Female	0.01223	0.01211	0.01218	0.00296	0.00294	0.00283
Race	White	0.01004	0.00994	0.01000	-	-	-
	Nonwhite	0.01441	0.01428	0.01436	-	-	-

Note: The table presents averaged EUT measures over various population subgroups. "Observed" refers to the indices calculated with observed covariate vectors while "Sim 1" and "Sim 2" refer to averaged obtained from counterfactuals where labor market conditions and household size in 2009 are replaced with the distributions in 2001.

Table 5 shows how average insecurity scores differ over population subgroups, and how the counterfactual simulations affect these subgroups. As illustrated above the changes in labor market conditions (Sim 1 - US) had a larger effect for lower income individuals, however women, non-white individuals, and younger, unmarried and divorced persons were also more strongly affected. This result would seem to suggest that the rise of part-time work and a reduction in working hours has mostly affected persons of lower socioeconomic status, as predicted by Standing (2011). However the result is not entirely unambiguous as persons with lower levels of educational attainments were no

more influenced than those with higher levels. Conversely the effects of the second simulation (Sim 2 - US) concerning shrinking household sizes are much more uniformly distributed. While women, older and widowed persons were more responsive than the rest of the sample the magnitudes of these effects are only slightly elevated. For Germany the results of these simulations are also relatively even. Younger people and women were more negatively affected by changes in the labor market (Sim 1 - GER) while persons over 60 were essentially unaffected. Similarly changes in household structure increased the insecurity of younger and unmarried persons disproportionately, but otherwise no particular subgroups stand out (Sim 2 - GER). Again these results are roughly consistent with expectations. Women and younger persons are more likely to be involved in casual or part time work, and hence an increasingly heavy reliance upon this form of income will increase insecurity. Similarly the trend towards smaller household sizes also implies a greater concentration of young and unmarried individuals living alone, which explains the rising insecurity within these groups.

5 Conclusion

This paper has presented some methodological and empirical contributions to the measurement of income insecurity. For fixed-effects panel data models we have shown that by making some assumptions on the functional form of regression equations, the distribution of residuals, the structure of any heteroskedasticity and the form of a welfare function, we are able to derive simple and convenient closed-form expressions for two commonly employed measures of risk based upon Expected Utility Theory. Further we have argued that as the concept of income insecurity has an implicit psychological component reference dependent utility measures offer scope for alternative indices that capture different facets of this complex problem. Despite the large number of modeling assumptions employed it can be seen that our approach is simply a convenient special case of a fairly general framework for measuring unpredictable risk exposure in panel data. For example the assumptions of normality/lognormality and the form of the welfare function could all be relaxed. Further, once an individual's predictive income distribution for the year ahead is known, there are many ways to model their risk exposure. While the techniques we employed here are applied frequently in this type of analysis, there are other methods such as Value at Risk (VaR) from the finance literature and Stochastic/Lorenz dominance from the inequality literature that could just as easily be implemented.

The empirical evidence we present paints a nuanced picture of the state of income insecurity in the US and Germany. For the US the story is simpler. Firstly, income insecurity is much higher than in Germany, a fact that persists over all four measures. As this is mostly due to a large constant term in its variance equation, we must look to factors that differ across countries but do not vary over individuals or time for an explanation. Differences in social welfare systems and labor laws appear to be suitable candidates. Secondly, income insecurity in the US appeared to rise fairly steadily over time, which can be traced in part to demographic factors such as changing household composition and an increasing non-white share of the population. However the largest single contributing factor was the time-trend which suggests again that factors outside our model remain the most important. We informally considered two possible explanations, an evolving political environment and an increase in the supply of low skilled labor, and found qualified support in both cases.

For Germany the results are less coherent. While both the level-based and change-based measures show increasing income insecurity after 2001, the trends are contradictory before this point, with the EUT measures declining and the RD measures increasing. Decomposing the trend in insecurity after 2001 revealed that the relative stability in estimates was the result of several determinants (mostly related to demographics such as aging and household composition) moving in offsetting directions, while our analysis of factors outside the model was largely uninformative. Lastly counterfactual simulations suggest that in both countries changes in labor market structure (captured by a trend towards part time work and fewer working hours) increased income insecurity and that the effects were felt disproportionately by persons of lower socioeconomic status. Similarly changes in household composition also raised insecurity however the magnitude of this effect was smaller and more evenly distributed across the population.

References

- Atkinson, A. (1970). "On the measurement of inequality" *Journal of Economic Theory*, 2, 244–263.
- Autor, D. Katz, L. and Kearney, M. (2005). "Rising Wage Inequality: The Role of Composition and Prices," NBER Working Paper No. 11628.
- Barberis, N. (2013). "Thirty Years of Prospect Theory in Economics: A Review and Assessment" *Journal of Economic Perspectives*, 27, 173–196.
- Bayaz-Ozturk, G. Burkhauser, R. and Couch, K. (2014). "Consolidating The Evidence On Income Mobility In The Western States Of Germany And The United States From 1984 To 2006," *Economic Inquiry*, 52, 431–443.
- Blinder, A. (1973). "Wage discrimination: Reduced form and structural estimates" *Journal of Human Resources*, 8, 436–455.
- Bossert, W. and D'Ambrosio, C. (2013). "Measuring Economic Insecurity," *International Economic Review*, 54, 1017–1030.
- Bourguignon, F. Ferreira, F. and Leite, P. (2008) "Beyond Oaxacañ Blinder: Accounting for differences in household income distributions," *Journal of Economic Inequality*, 6, 117–148
- Buhmann, B. Rainwater, L. Schmaus G. and Smeeding, T. (1988). "Equivalence scales, well-being, inequality, and poverty: Sensitivity estimates across ten countries using the Luxembourg Income Study (LIS) database" *Review of Income and Wealth*, 34, 115–142.
- Burkhauser, R. and Poupore, J. (1997). "A Cross-National Comparison Of Permanent Inequality In The United States And Germany," *The Review of Economics and Statistics*, 79, 10–17.
- Calvo, C. and Dercon, S. (2005). "Measuring Individual Vulnerability" Economics Series Working Papers 229, University of Oxford, Department of Economics.
- Catalano, R. (1991). "The health effects of economic insecurity," *American Journal of Public Health*, 81, 1148–1152.
- Dalton, H. (1920). "Measurement of the inequality of incomes" *The Economic Journal*, 30, 348–361.
- Dercon, S. (2005). "Risk, Poverty and Vulnerability in Africa" *Journal of African Economies*, Oxford University Press, 14, 483–488.
- DiNardo, J. Fortin, N. and Lemieux, T. (1996). "Labor Market Institutions and the Distribution of Wages 1973–1992: A Semiparametric Approach," *Econometrica*, 64, 1001–1044.
- Dynan, K., Elmendorf, D. and Sichel, D. (2007). "The Evolution of Household Income Volatility," Working Paper, Brookings Institution.
- Economou, M. Madianos, M. Peppou, L. Theleritis, C. Patelakis, A. and Stefanis, C. (2013). "Suicidal ideation and reported suicide attempts in Greece during the economic crisis," *World Psychiatry*, 12, 53–59.
- Elder, T. Goddeeris, J. and Haider, S. (2015). "Isolating the Role of Individual Covariates in Reweighting Estimation," *Journal of Applied Econometrics*, 30, 1169–1191.
- Feigenbaum, J. and Li, G. (2011). "Household income uncertainties over three decades," Finance and Economics Discussion Series 2011–25, Board of Governors of the Federal Reserve System.
- Ferrie J. (2001). "Is Job Insecurity Harmful to Health?" *Journal of the Royal Society of Medicine*, 94, 71–76.
- Firpo, S. Fortin, N. and Lemieux, T. (2007) "Decomposing Wage Distributions using Recentered Influence Functions Regressions," mimeo, University of British Columbia.
- Hacker, J. (2006). "The Great Risk Shift: The Assault on American Jobs, Families, Health Care, and Retirement and How You can Fight Back" Oxford University Press, USA.

- Hacker, J. Huber, G. Rehm, P. Schlesinger, M. and Valletta, R. (2010). "Economic Security at Risk: Findings from the Economic Security Index" Rockefeller Foundation, Yale University.
- Hardie, J. and Lucas, A. (2010). "Economic factors and relationship quality among young couples: comparing cohabitation and marriage" *Journal of Marriage & Family*, 72, 1141-1154.
- Journard, I, Pisu, M. and Bloch, D. (2012), "Tackling income inequality: The role of taxes and transfers", OECD Journal: Economic Studies, http://dx.doi.org/10.1787/eco_studies-2012-5k95xd6l65lt
- Kahneman, D. and Tversky, A. (1979). "Prospect Theory: An Analysis of Decision under Risk" *Econometrica*, 47, 263-291.
- Ligon, E. and Schechter, L. (2003). "Measuring Vulnerability," *Economic Journal*, 113, C95-C102.
- Maggi, M. (2004) "A Characterization of S-shaped Utility Functions Displaying Loss Aversion," Mimeo (http://www.mfn.unipmn.it/~maggi/maggi_files/usloss.pdf).
- Oaxaca, R. (1973). "Male-female wage differentials in urban labor markets," *International Economic Review*, 14, 693-709.
- Osberg, L. (1998). "Economic Insecurity" Discussion Papers 0088, University of New South Wales, Social Policy Research Centre.
- Rohde, N. K. Tang, and Rao, P. (2014). "Distributional Characteristics of Income Insecurity in the U.S., Germany, and Britain," *Review of Income and Wealth*, 60, S159-76.
- Rohde, N. Tang, K. Osberg, L. and Rao, P. (2016). "The Effect of Economic Insecurity on Mental Health: Recent Evidence from Australian Panel Data" *Social Science and Medicine*, 151, 250-258.
- Rothe, C. (2012): "Partial distributional policy effects," *Econometrica*, 80, 2269-2301
- Scheve, K. and Slaughter, M. (2004) "Economic Insecurity and the Globalization of Production," *American Journal of Political Science*, 48, 4, 662-674.
- Smith, T. Stoddard, C. and Barnes, M. (2009). "Why the Poor Get Fat: Weight Gain and Economic Insecurity" *Forum for Health Economics & Policy*, 12, 2.
- Smock, P. Manning, W. and Porter M. (2005). "Everything's there except money: How money shapes decisions to marry among cohabitators," *Journal of Marriage and Family*, 67, 680-696.
- Standing, G. (2008). "Economic Insecurity and Global Casualisation: Threat or Promise?" *Social Indicators Research*, 88, 15-30.
- Standing, G. (2011). *The Precariat*. London: Bloomsbury Academic. ISBN 9781849664554.
- Tashman, L. Bakken, T. and Buzas, J. (2000). "Effect of regressor forecast error on the variance of regression forecasts" *Journal of Forecasting*, 19, 587-600.
- Tversky, A. and Kahneman, D. (1992). "Advances in prospect theory: Cumulative representation of uncertainty". *Journal of Risk and Uncertainty*, 5, 297-323.
- Western, B. Bloome, D. Sosnaud, B. and Tach, L. (2012). "Economic Insecurity and Social Stratification" *Annual Review of Sociology*, 38, 341 - 359.

Appendix

Insecurity Estimates By Year

Table 6: Average Insecurity Estimates by Year - United States and Germany

Year	United States				Germany			
	I^{AT}	I^{DL}	I^{RD}	I^{EL}	I^{AT}	I^{DL}	I^{RD}	I^{EL}
1993	0.1015	0.0106	1.3635	1.0378	0.0296	0.0031	-1.2473	0.1877
1994	0.1098	0.0116	1.3614	1.0545	0.0292	0.0031	-1.0944	0.2123
1995	0.1031	0.0108	1.7746	1.1326	0.0287	0.0030	-1.1401	0.2207
1996	0.1010	0.0105	1.9133	1.1527	0.0293	0.0031	-0.9936	0.2439
1997	0.0929	0.0095	2.8138	1.1920	0.0286	0.0030	-1.0473	0.2569
1998	0.0988	0.0102	2.6550	1.1494	0.0288	0.0030	-0.8768	0.2706
1999	0.1046	0.0109	2.4962	1.1069	0.0290	0.0030	-0.7063	0.2842
2000	0.1043	0.0109	3.0587	1.1295	0.0283	0.0029	0.0272	0.2866
2001	0.1040	0.0108	3.6211	1.1522	0.0277	0.0029	0.7607	0.2890
2002	0.1061	0.0111	3.4209	1.1725	0.0286	0.0030	1.1878	0.2930
2003	0.1081	0.0113	3.2208	1.1928	0.0296	0.0031	1.6148	0.2971
2004	0.1079	0.0113	3.5148	1.1940	0.0294	0.0031	1.9108	0.2910
2005	0.1077	0.0113	3.8089	1.1952	0.0293	0.0030	2.2067	0.2848
2006	0.1083	0.0113	3.7476	1.1764	0.0291	0.0030	2.5928	0.2762
2007	0.1090	0.0114	3.6863	1.1576	0.0290	0.0030	2.9789	0.2676
2008	0.1106	0.0116	3.6658	1.1922	0.0293	0.0030	3.4337	0.2598
2009	0.1122	0.0118	3.6452	1.2269	0.0297	0.0030	3.8884	0.2519

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