



Griffith Business School

Discussion Papers | Economics

The Effect of Economic Insecurity on Mental Health: Recent Evidence from Australian Panel Data

Nicholas Rohde, Kam Ki Tang, Lars Osberg and D.S. Prasada Rao

No. 2014-06

Series Editor: Dr Nicholas Rohde and Dr Athula Naranpanawa

Copyright © 2014 by the author(s). No part of this paper may be reproduced in any form, or stored in a retrieval system, without prior permission of the author(s).

The Effect of Economic Insecurity on Mental Health: Recent Evidence from Australian Panel Data*

Nicholas Rohde[†], Kam Ki Tang[‡], Lars Osberg[§] and D. S. Prasada Rao[¶]

November 18, 2014

Key Words: Economic Insecurity, Instrumental Variables, Mental Health, Panel Data.

Abstract

This paper estimates the impact of economic insecurity on the mental health of Australian adults. Taking microdata from the 2001-2011 HILDA panel survey, we produce a conceptually diverse set of insecurity measures and explore their relationships with the SF-36 mental health index. By using fixed effects models that control for unobservable heterogeneity, and by exploiting exogenous fluctuations in economic conditions as an identification strategy, we produce estimates that correct for endogeneity more thoroughly than previous works. Our results show that exposure to economic risks has consistently detrimental health effects. The main novelty comes from the breadth of risks that are found to be harmful. Job insecurity, financial dissatisfaction, reductions in income, an inability to meet standard expenditures and a lack of access to emergency funds all adversely affect health. This suggests that the common element of economic insecurity (rather than idiosyncratic phenomena associated with any specific risk) is likely to be hazardous. Our preferred estimates indicate that a standard deviation shock to economic insecurity lowers an individual's mental health score by between 1.4 and 2 percentage points. If applied uniformly across the Australian population, such a shock would increase the morbidity rate of mental disorders by 2.5-3.8%.

1 Introduction

Economic insecurity has been a topic of recent interest in both academic literature and the popular press.

The concept refers to the anxiety felt by individuals when they are threatened by the prospect of severe

*This paper uses unit record data from the Household, Income and Labour Dynamics in Australia (HILDA) Survey. The HILDA Project was initiated and is funded by the Australian Government Department of Families, Housing, Community Services and Indigenous Affairs (FaHCSIA) and is managed by the Melbourne Institute of Applied Economic and Social Research (Melbourne Institute). The findings and views reported in this paper, however, are those of the author and should not be attributed to either FaHCSIA or the Melbourne Institute.

[†]Corresponding Author. Dept. Accounting, Finance and Economics, Griffith University, Australia. Email: n.rohde@griffith.edu.au. Ph + 617 555 28243. Nicholas Rohde, Kam Ki Tang and Lars Osberg are supported by the ARC Discovery grant DP120100204.

[‡]School of Economics, University of Queensland, Australia.

[§]Dept. of Economics, Dalhousie University, Canada.

[¶]School of Economics, University of Queensland, Australia.

economic losses, and emerging evidence suggests it is a major cause for concern. Survey data routinely shows that financial worries rank amongst the most troubling for households,¹ and related problems have been associated with social ills including familial breakup (Larson et al., 1994), depression (Tsutsumi et al., 2001; Meltzer et al., 2009), and suicide (Hintikka et al., 1999; Blakely et al., 2003). The importance of economic security has also been emphasized by Stiglitz et al. (2009) who argue that it should be considered as a part of measures of economic performance and social progress; and by the United Nations which declares economic security a fundamental human right.² Further, there is evidence that economic insecurity has been intensifying over recent years,³ a trend which predates the last global recession. In most countries measures of consumer confidence have been declining since the late 1990s,⁴ while studies by Hacker (2006), Hacker et al. (2010), Osberg and Sharpe (2002), Sharpe and Osberg (2009) and Nichols and Rehm (2014) show that this downward trend has been matched by increases in household level economic risk.

This paper models the impact of economic insecurity upon the mental health of Australian adults. There are three primary objectives. The first is to generalize findings from the extant literature on risk exposure and health by showing that negative effects are not limited to one or two specific forms of risk, such as job insecurity or the threat of destitution. Rather there are mental health consequences associated with a wide variety of economic hazards, which suggests that the underlying prospect of monetary loss is likely to be an important contributing factor. Secondly the paper addresses a methodological limitation present in some of the previous research. As economic insecurity is likely to be both a cause and a consequence of poor mental health, regular statistical estimates of this relationship will be biased due to endogenous feedback effects. This problem is circumvented by using exogenous fluctuations in an individual’s economic environment as an identification strategy, and by employing panel data models which can control for unobserved time invariant individual heterogeneity. Lastly, the paper aims to quantify the effect that changes in economic insecurity would have on the mental health of the Australian population. By aggregating results over individuals, the paper simulates the effects of economy-wide shocks on the morbidity rates of psychological disorders.

2 Background

There exists an extensive body of literature linking health status with certain forms of risk exposure. Although individuals face a wide variety of potential economic hazards, much of this research has focused on the

¹See for example research by Gallup (www.gallup.com) and the international General Society Survey (<http://www3.norc.ox.ac.uk/gss+website>).

²See Article 25 of the 1948 United Nations’ Universal Declaration of Human Rights.

³Hacker et al. (2010) and the OECD (2004) both report on trends in job security.

⁴For the US see the Michigan Survey of Consumer Confidence. Australian data comes from the Westpac - Melbourne Institute Survey of Consumer Sentiment while data from the United Kingdom and Canada come from GfK NOP. Similar trends are also visible in Euro area consumer confidence data coming from the European Commission.

effects of labor market insecurity. Early works by Sverke et al. (2002), De Witte (1999), Ferrie (1998a, b), McDonough (2000) and Cheng et al. (2005) (and many others) have shown that job insecurity is robustly linked to diminished health. More recent studies have expanded this thesis by (i) examining specific aspects of the insecurity/health nexus, and (ii) by employing sophisticated statistical techniques to disentangle causes from effects.⁵ Notable works include Green (2011) who links insecurity to broader issues such as happiness and re-employability; Slopen (2012) who considers long-term health effects; and László et al. (2010) and Caroli and Goddard (2013) who examine consequences for heavily protected European workers. Further research by Luechinger et al. (2009) shows that job insecurity has broad societal effects while Landsbergis et al. (2012) find that insecurity is a significant source of health inequality.

Despite this considerable volume of research, the precise causal mechanism underpinning these relationships remains poorly understood. This uncertainty occurs because job losses and other negative economic shocks are often multifaceted phenomena, combining economic (i.e. monetary) disturbances with other social determinants of stress. These social stressors are often hard to quantify, but may be more important than economic losses in their effects upon psychological health. For example an individual with an insecure job faces the potential for lost income, however they also risk a sense of humiliation associated with sacking (Fryer and Fagan, 2003), feelings of purposelessness due to unemployment (Kessler et al., 1989) and social isolation from former colleagues (Lim, 1996). Similarly mortgage foreclosure is known to deteriorate health (Cannuscio et al., 2012) which may be due to financial strain, or to coincidental factors such as the stress of home relocation (Raviv et al., 1990). As social/contextual stressors such as these frequently occur simultaneously alongside economic shocks, it is difficult to identify which are the true sources of mental strain. Indeed it is possible that the threat of economic loss is relatively benign for health, and that it is these other factors that have driven the results found in the empirical literature.

Determining which components of economic risk exposure are harmful for mental health is important from an epidemiological point of view, and for the formulation of policy. If it is the prospect of economic hardship that is damaging, then threats to income or wealth will have widespread effects upon population health, as virtually all individuals will face some exposure to these types of risk. In this instance policies that protect against economic losses such as stronger labor market regulations and more extensive social safety nets could be expected to be beneficial. Conversely if it is the social or non-monetary aspects of risk exposure that are damaging, this suggests a subtler and more complicated relationship between economic stability and health. Such a finding would require a reinterpretation of the risk/health literature and would imply that social insurance mechanisms may be ineffective in buttressing psychological wellbeing. In this case further

⁵Studies by Ferrie et al. (1998a, b) stand out in particular for their creative methods for handling endogeneity.

research into the specific idiosyncratic causes would be needed such that health-orientated policies could be appropriately targeted.

The main goal of this paper is to determine the role that the economic aspects of risk exposure play in determining health. This requires measuring economic insecurity, which has typically presented a challenge to social scientists as the contribution of economic risk to an individual's sense of stress is inherently unobservable. However the concept can be operationalized by measuring specific phenomena that are likely to be stressful and combining these indicators with the aim of inferring the resultant sense of anxiety. Economic insecurity is thus seen as a multidimensional concept that includes (alongside job insecurity) the risk of poverty (Bandyopadhyay and Cowell, 2007; Calvo and Dercon, 2013), income volatility (Barnes and Smith, 2009; Smith et al., 2011; Rohde et al., 2014), bankruptcy (Kalleberg, 2009), loss through family dissolution, crime or widowhood (Western et al., 2013; Osberg and Sharpe, 2002), wealth dynamics (Bossert and D'Ambrosio, 2013; D'Ambrosio and Rohde, 2014) and lack of access to insurance, in particular health insurance (Dominitz and Manksi, 1997; Bucks, 2011; Hacker, 2006; Hacker et al., 2010). At the aggregate level phenomena such as business cycles (Stuckler et al., 2011) and exposure to international competition (Scheve and Slaughter, 2004; Standing, 1997) are also relevant.

While this multifaceted approach cannot explicitly identify the aspects of risk exposure that damage mental health, it does provide scope for narrowing the field of candidate explanations. The economic, or *monetary* explanation predicts that all risks that have an individual or household-level financial element should have adverse health implications. Conversely the incidental, or *non-monetary* explanation predicts that only risks that also provoke negative social responses should be harmful. We may therefore gain an appreciation as to how important the economic aspects are by searching for consistency in effects across differing forms of risk exposure. If a large and diverse set of economic risks is found to have negative causal impacts (especially if these impacts are of similar magnitudes) this would suggest that the common monetary element plays a fundamental role. However if only some economic risks are harmful, and if there is a large degree of variation in the way that health responds to differing risks, this would suggest that there were other risk-specific phenomena besides monetary risk that are more important. Of course there are limitations with such an approach as it is possible that both monetary and non-monetary factors could measurably influence health, that there are non-monetary effects associated with all hazards, or that individuals have differing sensitivities to alternative types of monetary risk. Nonetheless in the absence of quantitative data on the multitude of social dimensions of economic stress, such a method can take a step towards clarifying this important issue.

3 Data

We take data from the HILDA (Household Income and Labour Dynamics in Australia) survey which is a high quality panel comparable to the US based PSID or German SOEP data sets. The survey has followed almost 20,000 individuals over 11 years to date⁶ (from 2001 to 2011) and asks an extensive range of questions on health, incomes, demographics, life events and labor market experiences. Individual level data are used (although persons are grouped by households in some instances) and we match observations through time such that each person can be followed over the course of the period.

Health data comes from the SF-36 survey which is a widely used generic multi-item health assessment tool (Bowling, 1997). The variable is obtained from 36 questions relating to eight different facets of physical and mental health⁷ where the responses are aggregated to give each individual a score from 0 to 100 (Ware et al., 2000) such that higher scores indicate better health perceptions. The SF-36 is often partitioned into a physical functioning variable and a mental health variable, both of which operate in the same manner as the overall SF-36. We use the mental health index which quantifies respondent vitality, social functioning, emotional functioning and anxiety/depressive symptoms. The index is routinely modeled as a continuous variable and is taken in every wave in the HILDA survey. Only adults fill in the mental health questionnaire on the HILDA survey and hence our analysis applies only to people aged 18 and over.

In addition to the mental health indicator a number of other variables are taken to measure economic insecurity. These include standard variables such as employment status and income, but we also use subjective questions on financial satisfaction, feelings of job insecurity, and the perceived ability of householders to raise emergency funds. Dichotomous variables that indicate whether or not individuals could meet standard expenses such as rental repayments or utility bills are also employed. Further a number of variables that may be associated with mental health are taken as controls. Data on age, education, household size, marital status, an indicator of geographic remoteness, and measures of social integration⁸ and physical functioning all serve to account for extraneous determinants of mental health. Household income is measured in “disposable” terms⁹ using 2011 Australian dollars and is standardized by the square root of the household size (Buhmann et al., 1988) while education is measured in years of formal schooling. We also use dummy variables to control for the impact of important life events occurring in the previous 12 months including marriages, separations, pregnancies, births, deaths of family members and victimhood of physical violence. In total the range of

⁶The first wave consisted of 19,914 individuals and has since been topped up with an additional 5,477.

⁷The eight facets are (1) vitality, (2) physical functioning, (3) bodily pain (4), general health perceptions, (5) physical role functioning (6) emotional role functioning (7) social role functioning and (8) mental health.

⁸This variable asks for the respondent to assess the strength of their social lives.

⁹This is the sum of household income minus total taxes.

control variables is large and captures most of the social drivers of stress or anxiety (Mirowsky and Ross, 1989).

Lastly a set of instruments is developed in order to isolate causality flowing from insecurity to psychological health. Rather than focusing on the insecurity of each individual as measured, our estimation procedure only uses variations that are directly attributable to changes in each person's economic environment. As fluctuations in economic conditions are common and are not related to any single individual's mental state, they can be treated as exogenous variations that can identify our parameters of interest. Such an approach is similar to the identification techniques employed by Barnes and Smith (2009) and Smith et al. (2009) who use differentials in unemployment rates to identify endogenous parameters in cross-sectional regressions. To gauge the general economic environment three instruments are developed by averaging indicators of economic risk across demographic subsets of the sample. These are the unemployment rate by age bracket, the average level of financial satisfaction by educational qualification, and the average job insecurity of the region. In each case the qualitative variable (age, education, regional code) divides the sample into 10-16 subgroups and an expected value is taken for each bracket/year. To avoid simultaneity we ensure that the averages depend on large sample sizes of between 100-2000 observations per bracket/year and exclude the scores of each specific individual when evaluating their subgroup average.¹⁰ Some brief summary statistics of all variables and instruments and some distributional plots are available in Appendices A1 and A2.¹¹

The following notation is used throughout the paper. Our mental health index is denoted with the matrix M such that M_{it} refers to the score of the i th individual in period t . Additionally J insecurity measures are used and these are EI^1, EI^2, \dots, EI^J where EI_{it}^j has the same interpretation as above. Furthermore our regressions employ X'_{it} as a row vector of Q control variables and Z'_{it} as a vector of v exogenous instruments. Variables from specific cross sections will be referred to as x_{qt} and z_{vt} where q and v denote the specific variable for the control and instrument cases respectively. Income is a variable of particular interest as it is used to obtain certain insecurity measures and will be denoted with the vector \tilde{x}_t .

¹⁰The validity of the instruments is examined in later sections and the approach is found to be sound in the strong majority of cases. See column 8 of Tables 1 and 2.

¹¹An important assumption in any panel data econometrics is that missing values are random rather than determined with reference to the data set. We search for evidence against the Missing at Random (MaR) hypothesis by comparing variable means and standard deviations before and after the missing values for a second variable are excluded. As this has little impact upon the distributions we informally conclude that the missing values problem will not unduly affect our results.

4 Measuring Economic Insecurity

To measure economic insecurity we employ a basket of proxy indicators designed to capture differing aspects of risk exposure. Conceptual diversity between the measures is paramount here, as we wish to ensure that our results are not being driven by some confounding factor that is specific to a particular type of risk or measurement concept.

To quantify insecurity appropriately, it is necessary to consider some desirable properties for an index to exhibit. Ideally a measure should (i) reflect some potentially stressful economic risk, (ii) be *prospective* rather than retrospective, and (iii) be *personal*, meaning that it is sensitive to individual differences in temperament and attitudes to risk. Practically it can be difficult to produce measures that satisfy these criteria, with only subjective surveys of individual level economic perceptions reliably meeting all three. Despite this, there are also roles for objective measures of economic risk which are less personal but more easily interpretable. Objective measures that have been employed in the literature have tended to either focus explicitly on the instability of income, or measure the probability of some hazardous event such as unemployment occurring. This paper uses all three types of measures (subjective surveys, income instability measures and probabilistic hazard indices) and we provide details of each in the following sections.¹²

Subjective Indicators

There are three subjective questions in the data set that capture important aspects of economic insecurity. The first question asks the individual to evaluate their feelings of security in their main form of employment. The second question asks for an all-things-considered overall level of financial satisfaction, and a third measure asks respondents how easily they could raise emergency funds if needed. Although all the variables are ordinal each is interpreted with a linear scale. When appropriate we invert the indices such that higher scores imply greater risk. The measures are denoted

$$EI_{it}^1 = 8 - JS_{it} \tag{1}$$

¹²An important caveat with all such approaches however is that they tend to omit important information and hence require some assumptions on the role that economic risk plays in producing anxiety. For example an individual with a high subjective or objective exposure to risk may not feel insecure if the risk is in line with their preferences, or if they have access to suitable mitigation or avoidance mechanisms. Further individuals may feel exposed to other forms of risks that are not explicitly considered, and hence specific measures may miss important aspects of the problem. As these characteristics cannot be controlled for, we assume that they can be averaged out across a sample such as not to bias statistical estimates.

$$EI_{it}^2 = 10 - FS_{it} \quad (2)$$

$$EI_{it}^3 = EF_{it} \quad (3)$$

where $EI_{it}^1 \in \{0, 1, 2, \dots, 10\}$, $EI_{it}^2 \in \{0, 1, 2, \dots, 10\}$ and $EI_{it}^3 \in \{1, 2, \dots, 4\}$ measure *job insecurity*, *financial dissatisfaction* and ability to raise *emergency funds* respectively; and JS , FS and EF are the variables from the HILDA data set.

Income Stream Indicators

In addition to the subjective questionnaire variables, we use two objective indicators based on income streams. Income based indicators typically measure negative instability and have been used as a basis for measurement by Hacker et al. (2010), Rohde et al. (2014) and Nichols and Rehm (2014). The central idea is that volatility, and in particular downward movements, will highlight an unreliable income and therefore capture an important aspect of insecurity. We employ a dichotomous variable that takes on a value of 1 for all individuals within a household if their income (i) drops more than 25% from the previous period, and (ii) is lower than their average income over the 11 waves. This *income drop* variable relies upon being a predictor of future distress for prospective relevance and is given as

$$EI_{it}^4 = \begin{cases} 1 & \text{if } \tilde{x}_{it} < 0.75 \times \tilde{x}_{it-1} \text{ and } \tilde{x}_{it} < \frac{1}{T} \sum \tilde{x}_{it} \\ 0 & \text{otherwise} \end{cases} \quad (4)$$

A second measure based on income dynamics is a *level-and-change* (LEC) index inspired by the recent work of Bossert and D'Ambrosio (2013), who are the first authors to provide a solid axiomatic foundation for economic insecurity. Their method is based upon household wealth streams, however as wealth is not a regular feature of our data we apply their ideas to income instead, but note that this involves a substantial departure from the original intended use. Our index treats insecurity as a function of current income and a weighted sum of the differences between lags $\tilde{x}_{it-1}, \tilde{x}_{it-2}, \dots, \tilde{x}_{i1}$ and combines these two components with a time discounted weighting function that emphasizes the recent over the distant past. An asymmetric weight is also used to emphasize downward movements in line with the theory of loss aversion of Kahneman and Tversky (1979). The index can be written as

$$EI_{it}^5 = -\tilde{x}_{it} + \sum_{l=1}^L \alpha(l) \Delta_l(\tilde{x}_{it}) + \sum_{l=1}^L \beta(l) \Delta_l(\tilde{x}_{it}) \quad (5)$$

where $\Delta_1(\tilde{x}_{it}) = (\tilde{x}_{it} - \tilde{x}_{it-1})$, $\Delta_2(\tilde{x}_{it}) = (\tilde{x}_{it-1} - \tilde{x}_{it-2})$ etc, $l = 1 \dots L$ is the lag length and set equal to a maximum value of three, and

$$\alpha(l) = \begin{cases} \frac{\gamma}{2l-1} & \text{if } \Delta_l(\tilde{x}_t) < 0 \\ 0 & \text{if } \Delta_l(\tilde{x}_t) > 0 \end{cases} \quad \text{and} \quad \beta(l) = \begin{cases} \frac{\alpha(l)}{2} & \text{if } \Delta_l(\tilde{x}_t) > 0 \\ 0 & \text{if } \Delta_l(\tilde{x}_t) < 0 \end{cases}$$

where $\alpha(l)$ and $\beta(l)$ come from the inverse Gini social evaluation functions given in Donaldson and Weymark (1980) and Weymark (1981). Lastly $\gamma > 0$ is a parameter that weights between levels and changes, and a fixed $\gamma = 5$ is used to emphasis the change component. The index is homogenous of degree one in income and has support on \mathbb{R}^1 where higher values indicate greater insecurity.

Hazard Probability Indicators

To complete the basket, three probabilistic measures are employed based on the chance that an individual will experience an adverse financial event in the coming year. Let y_{it} be a generic dichotomous indicator of (i) unemployment for the individual at the time of the survey, and (ii) experiencing an income drop of the type defined in Eq (4). A prospective measure is then the probability of either event occurring in the *next* wave of the data. To model this we take a probit specification and produce forecasts for these hazards occurring. The indices are then $E_{it}^6 \in [0, 1] = \hat{y}_{it+1}$ where y_{it+1} is determined on the basis of unemployment and $E_{it}^7 \in [0, 1] = \hat{y}_{it+1}$ when y_{it+1} comes from the income drop variable EI_{it}^4 . The measures therefore give respectively the predicted *probability of unemployment* next year and the predicted *probability of an income drop* of the type defined in Eq (4).

The same idea is used to construct a measure of distress based upon other sources of financial strain such as the inability to meet standard expenses. We use dummy variables to indicate (i) an inability to pay utility bills (electricity, gas, telephone), (ii) a failure to make a rental or mortgage payment, (iii) pawning or selling household items and (iv) going without meals. The dummy variables are aggregated and an ordered probit then forecasts the probability that an individual will exhibit either 3 or 4 of the above signs of *expenditure related stress* in the forthcoming year.¹³ This last measure is denoted $EI_{it}^8 \in [0, 1]$.

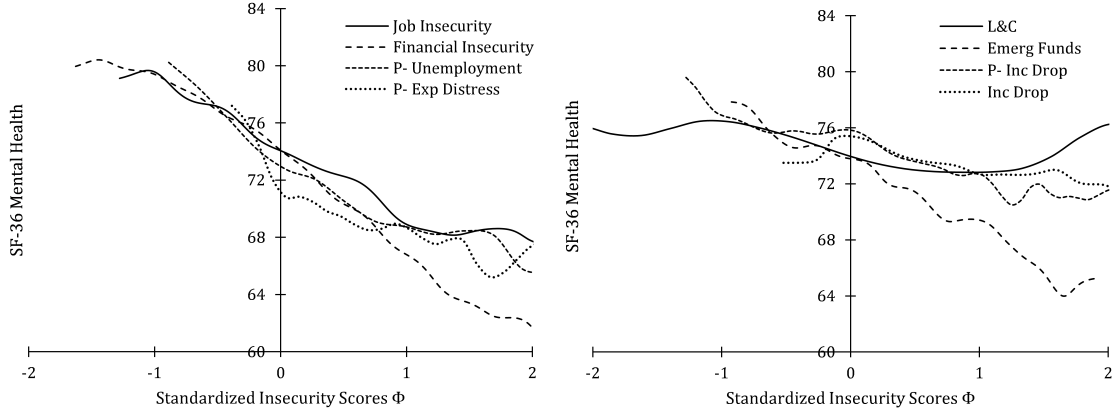
¹³It is assumed that the pawning or selling of household items is done to finance short term expenses.

Once established, the above basket of indicators allows us to consider a variety of threats to economic wellbeing. An important point of caution however is that as economic insecurity is a latent phenomenon, it is unknown how well the measures are serving their intended purposes. However as the measures are all quantifying aspects of the same intrinsic problem, we can check their performance by searching for consistency across the range of indicators. In Appendix A3 we show that in *all* $J(J+1)/2 = 28$ pairwise cases the indices are positively correlated, while empirical copula densities indicate high concentrations of individuals exist in both tails of bivariate insecurity distributions. Thus it appears that the measures are all appropriately related which reinforces the notion that insecurity is being suitably measured.

5 Model Specification and Results

The purpose of the paper is to model the causal relationships between each $EI^1 \dots EI^J$ and M , and to look for similarities/differences across these relationships. Initially however it is useful to examine the raw associations to gain an appreciation of the size of the underlying dependencies. All eight measures coincide with diminished mental health (see the correlations presented in Table 8 of Appendix A3) while Figure 1 shows kernel regressions of mental health against the insecurity measures. As the indices are distributed differently with diverse units of measurement, each is transformed by taking the between-individual variation, mean differencing and dividing through by the standard deviation. This gives each index a standard-deviations-from-mean interpretation denoted Φ . To produce the regressions we use the Nadaraya (1964) - Watson (1964) estimator to extract the underlying relationships.

Figure 1: Within-Individual Variation of Mental Health Scores with Economic Risk Indicators



Note: The horizontal axes give the insecurity measures defined in terms of standard deviations from the mean while the vertical axes give the SF-36 Mental Health summary index. All estimates are based upon between-individual variation taken over the full 11 year panel.

Figure 1 illustrates the negative associations between each measure and individual mental health. Both sets of curves indicate that psychological health is disproportionately lower in persons who are economically insecure. Comparing the separate regressions shows a degree of unanimity between the results which suggests psychological wellbeing is approximately equally sensitive to the different dimensions. These lines have fairly constant average slopes from -2 to -4 units per standard deviation, a figure which also corresponds to 2-4 percentage points of its maximum value. An exception is the L&C index which shows only a vague negative association with mental health.

Parametric Regressions

Given that greater levels of insecurity coincide with poorer mental health, our task is to estimate the relationships while controlling for extraneous factors, in particular the current income of the individual in question. By stripping out the income effect we allow insecurity to be unrelated to current material comfort, leaving the insecurity measures to act purely as risk indicators. Throughout the paper the Fixed Effects (FE) model is used

$$M_{it} = \alpha_i + X'_{it}\beta + \phi^j EI_{it}^j + \varepsilon_{it} \quad (6)$$

where α is an $n \times 1$ dimensional vector of individual effects, β is a $k \times 1$ dimensional vector of parameter estimates, ϕ^j is a scalar coefficient on EI_{it}^j and ε_{it} is an error term. While it would be possible that α

may be uncorrelated with X_{it} (and hence a Random Effects (RE) model with error term $\bar{\alpha} + u_i + \varepsilon_{it}$ may be applied) on the basis of endogeneity tests (Hausman, 1978; Wu, 1973) we will only report results from FE estimates. These have the benefit of controlling for individual specific time invariant heterogeneity and therefore do not suffer from many of the endogeneity problems that plague most econometric models. The models are estimated twice, firstly under the strict endogeneity assumption $E(e_{it} | X_{i1}, \dots, X_{iT}) = 0$ and secondly employing Instrumental Variable (IV) estimators relying on the weaker assumption $E(e_{it} | z_{it}) = 0$. Both models are fitted using the Generalized Method of Moments (GMM) (Hansen, 1982; Schaffer, 2010) and to account for potential heteroskedasticity and cluster effects (i.e. $\text{Cov}(\varepsilon_{is}, \varepsilon_{it}) \neq 0$ for $s \neq t$) panel robust standard errors are employed allowing for clustering by individual.

Table 1: Causal Impacts of Economic Insecurity on SF-36 Mental Health

Variable	$\hat{\phi}_{FE}^j$	$\hat{\eta}_{FE}^j$	$\hat{\phi}_{FE/IV}$	$\hat{\eta}_{FE/IV}^j$	R_w^2	n	K-P F	H χ_{V-1}^2
Job Insecurity - EI^1	-0.710***	-0.029	-0.866	-0.035	0.0433	11278	56.159	0.7910
Financial Dissat - EI^2	-0.788***	-0.038	-0.522*	-0.025	0.0513	107412	163.56	0.1586
Emergency Funds - EI^3	-1.182***	-0.028	-1.282**	-0.031	0.0452	106122	211.87	0.3132
Income Drop - EI^4	-0.438***	.0004	-7.132***	0.008	0.0094	14036	55.335	0.2091
L&C Index - EI^5	8.0E-07	-	1.9E-5	-0.008	0.0257	12921	54.614	0.1321
P - Unemployment - EI^6	-42.71***	-0.011	-82.66	-0.020	0.0339	10687	58.81	0.6081
P - Income Drop - EI^7	-5.423***	-0.009	-4.277**	-0.007	0.0377	9015	1304.6	0.9284
P - Exp Distress - EI^8	-13.02***	-0.004	-21.14	-0.007	0.0353	44281	8.629	0.7151

Note: The first two columns refer to estimates from the standard FE model while the remaining columns refer to the IV regressions. Parameter estimates for ϕ^j and elasticities-at-means η are given in the four leftmost columns. The fifth column gives the within R^2 statistic and the sixth column shows the number of individual observations. The seventh and eighth columns provide the Kleibergen-Paap (2006) F statistic for weak instruments in the presence of heteroskedasticity (adapted from the more standard Cragg-Donald (1993) test) and the P -value of the robust Hansen (1982) test for overidentification. All regressions employ control variables: income, age, education, marital status, household size, a rural/urban indicator, a social satisfaction variable, a physical health summary index, and life event dummies for marriage, separation, pregnancy, birth and victimhood of violence.

Estimates of $\phi^1 \dots \phi^J$ from each model are given in Table 1 and provide the central focus of the paper. Columns 1 and 2 give parameter estimates and elasticities for every measure from the regular FE model, while columns 3 and 4 do the same for the instrumented indices. The regular FE estimates show all risk measures besides the L&C index affecting health in the anticipated direction, indicating that increased insecurity leads to lower mental health under our first set of exogeneity assumptions. These estimates are all significantly different from zero at 1% and hence we can strongly reject the notion that sampling variation is the source of this result.

Under the second set of exogeneity assumptions (which yielded the IV estimates) we note that the coefficients are negative for seven of the eight cases, and four of these seven models also reject the null hypothesis of $\phi^j = 0$. Thus over both sets of estimates, the frequent rejection of this null indicates that mental health is sensitive to a wide variety of economic risks. Indeed the breadth of this finding suggests that the measures may all be reflecting the same (or very similar) underlying phenomena. It is worth noting that aside from being

indicators of monetary risk exposure, the measures have little in common with each other. Once the financial aspect is removed, the experience of feeling insecure in one’s job is rather unlike lacking access to emergency funds, or having a high probability of failing to meet basic expenses in the coming year. Consequently it appears that the mutual aspect of economic risk exposure may be behind all of these findings, rather than each being independently caused (to similar degrees, as shown in Section 6) by the unique sets of non-monetary phenomena that accompany each specific risk.

Specification and Robustness Checks

The validity of the results presented in Table 1 relies upon a set of modeling assumptions that are investigated below. Initially we search for signs of misspecification by examining the signs of the parameter estimates on the control variables. In the above regressions, income, education, household size, self-rated physical health, family births, pregnancies and social integration generally had positive (and significant) coefficients, while separation, family deaths and victimhood of violence generally had negative coefficients. Given that the models are returning anticipated results Eq (6) has no immediate signs of misspecification across the regressions.

To check for robustness, an informal testing procedure is also given in Appendix A4. If parameter estimates are highly dependent on the choice of covariates this may be interpreted as a lack of structural validity and casts doubt upon the strength of the results (Lemar, 1983; White and Lu, 2010). Here the method outlined by Barslund et al. (2007) is used where the explanatory variables are partitioned into a critical core (the instrumented insecurity index), an outer core set regarded as essential in the estimations, and a peripheral set. The equations are then re-estimated while omitting all possible combinations of the peripheral set, while the magnitude of the critical core variable is observed.¹⁴ Results are reported in Table 7 (Appendix 4) which show that the auxiliary estimates of $\phi_{FE/IV}^j$ very rarely changed signs and tended to lie on a $\pm 2\sigma$ interval, and hence it is concluded that the results are robust to inclusion/exclusion of peripheral variables.

¹⁴ In all cases we use household size, marital status, education and the household remoteness index as peripheral variables.

Instrumentation Tests

The validity of the identification strategy used for the IV estimates also requires testing. Firstly Kleibergen-Paap (2006) tests for weak instruments are used to check the identification of the models, and the test statistics generally exceed the rule-of-thumb score of 10 indicating suitable correlations between the instruments and the insecurity measure. We also perform the overidentification test given by Hansen (1982) which tests the null that z_{it}^v is uncorrelated with the error term and is correctly excluded from the regression equation. Rejection of this null casts doubt over the exogeneity of the instruments and is of considerable importance given that the instruments used are obtained from some of the same source data as the insecurity measures. Fortunately the Hansen test fails to reject the null in all cases. This is consistent with the flow of causality posited where fluctuations in economic conditions occur exogenously, causing variations in economic insecurity which in turn affect mental health.

Considering the results of these diagnostics we now isolate two sets of estimates that pass all our diagnostic criteria. For the uninstrumented estimates the coefficients were generally robust and had control variables of the expected signs, with only the L&C index not significant. For the instrumented estimates we eliminate the L&C index, the job insecurity measure and the probabilities of unemployment and expenditure distress, which were not significant at standard levels.

6 Interpretation of the Magnitude of Effects

Based upon our preferred sets of estimates outlined above we now wish to consider the size of the effects across our baskets of measures. As emphasized above, similar results across the measures would be consistent with a single common cause captured equally by all measures, while a large degree of variety would suggest that the measures were capturing differing phenomena besides economic insecurity that were also relevant for health. However as the indices do not have the same units of measurement this section provides a basis for uniform comparisons between the effects of the insecurity indices and gives an intuitive representation of their impacts on mental health.

Elasticities and Standard Deviation Shocks

One way of comparing estimates with each other is to consider the elasticity-at-means estimates reported in the second and fourth columns in Table 1. The estimates indicate that a 1% increase in insecurity leads to a decline in the mental health scores of around 0.01-0.03%, depending on the measure specified. As elasticities do not account for the differing degrees of variation in each measure, Table 2 simulates the effect of a one standard deviation shock to each insecurity score. The columns show the effect on mental health of such a shock in terms of units of the dependent variable (i.e. $\hat{\sigma}_{EI^j} \times \hat{\phi}^j$). Figures in bold denote estimates that are (i) significant and robust in the case of the uninstrumented regressions, and (ii) from the instrumented equations that also satisfied our additional diagnostic criteria.

As Table 2 indicates, a shock of a single standard deviation to each measure has a fairly uniform effect on the M scores. For the regular FE estimates the bolded impacts upon the SF-36 tend to congregate around -1 to -1.3 units per standard deviation. For the instrumented estimates that satisfied our diagnostic criteria, the results cluster around -1.4 to -2 points in terms of unit changes. Thus while there are slight differences in estimates produced using the alternative procedures, there is little indication that the effect sizes vary wildly from one risk concept to the next. Indeed the most atypical significant estimate in the first row (on EI^4 - the income drop index) becomes highly consistent with the other indices when instrumented, while the most divergent instrumented index (on EI^6 - the objective unemployment risk measure) has a very typical parameter size once the instruments are removed. Once some allowances for sampling variation are made, the reasonable degree of consistency across these results suggests that the mental health costs of economic insecurity are not driven by acute factors specific to any particular hazard, measurement concept or econometric technique.

Table 2: Sensitivity of Psychological Health Scores to Insecurity Measures

SF-36 Mental Health Score	EI^1	EI^2	EI^3	EI^4	EI^5	EI^6	EI^7	EI^8
Response of $SF36$ to $\hat{\sigma}_{EI^j}$ (FE)	-1.206	-1.792	-1.252	-0.119	0.075	-1.110	-0.494	-1.042
Response of $SF36$ to $\hat{\sigma}_{EI^j}$ (IV)	-1.470	-1.198	-1.360	-1.938	1.783	-2.558	-0.390	-1.691

Note: Each column gives insecurity indices EI^1 - EI^8 . The first row shows the response of M to the indices without instrumentation, while the second row gives the same estimates in the instrumented cases.

Assuming that these risk measures are capturing the same latent variable, it is useful to be able to make stylized comments on the general effect of this phenomenon. To accomplish this we calculate the mean impact of the standard deviations shock across the set of bolded estimates with the aim of producing a generic indicator of economic insecurity. For the uninstrumented estimates this is around -1.02 units per averaged

standard deviation shock while for the instrumented estimates this is -1.76. Given that the instrumented estimates represent a superior method of controlling for endogeneity we treat this figure as a representative summary estimate in the next section.

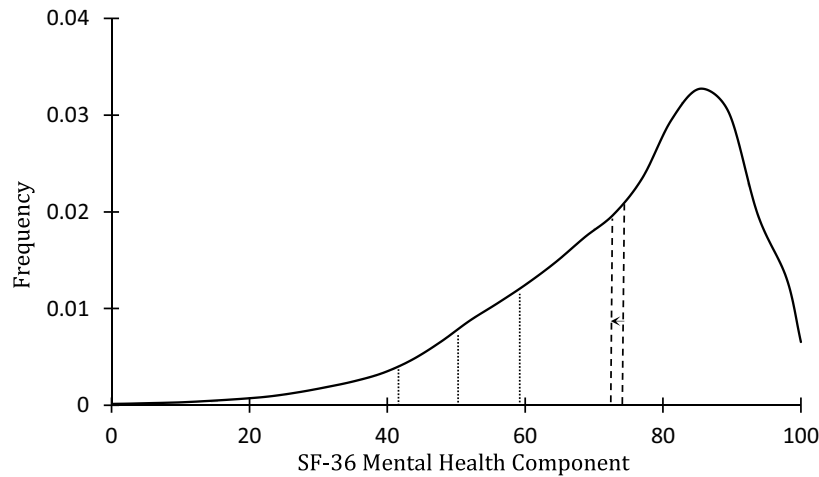
How Damaging is Economic Insecurity for Public Health?

In order to appreciate the impact that economic insecurity has upon public health, it is desirable to consider how large a -1.76 unit decline in the SF-36 mental health index is. To reinforce the size of this stylized effect, we exploit a close parallel between the SF-36 mental health index and a similar mental health variable, the K10 Kessler score (Kessler et al., 2002). These indices are highly correlated (around 0.8) but the K10 index has the advantage of possessing discrete groupings ranging between “likely to be well” to “likely to be suffering a severe mental disorder”. By taking the percentiles at which individuals fall into these categories on the K10, we can develop similar categories for the SF36.¹⁵ We then consider the number of shocks to insecurity required to push an average individual to the thresholds of these categories.

As the size of these shocks is best understood relative to the distributions of mental health scores the density of SF-36 scores must be modeled. We use an adaptive two stage kernel process which performs well when the true distributional form is unknown. Once the bandwidth is determined a (first stage) pilot density is estimated which guides the second-stage adaptive kernel. A standard approach is to use the Abramson (1982) estimator which defines a scaling vector $\lambda_i = \lambda(V_i) = \left(G/\hat{f}_h(MH)\right)^{0.5}$ with $G = \left[\prod_{i=1}^n \hat{f}_h(MH_i)\right]^{\frac{1}{n}}$. This allows the bandwidth to vary (i.e. $\hat{h}_i = \hat{h} \times \lambda_i$) such that the estimator has a large bandwidth when data are sparse and a small bandwidth when closely packed. To account for biases around support boundaries the data reflection approach (Schuster, 1985) is used and the density is estimated over an unrestricted domain. Figure 2 gives the PDF with the stylized standard deviation shock depicted.

¹⁵The K10 is only available in three waves of the HILDA panel and therefore cannot be used in place of the SF-36 for the full analysis.

Figure 2: Impacts of a One Standard Deviation Insecurity Shock on SF-36 Mental Health Summary Index



Note: The figure gives the distribution of M scores where the dashed lines depict (i) the means of each distribution, and the shifts associated with a one standard deviation shock using the stylized sensitivity of 1.76 units. Conversely the dotted lines show the percentiles at 19%, 11% and 5% which correspond to the empirical frequencies of individuals in the “mild”, “moderate” and “severe” groupings according to the Kessler thresholds.

The dashed vertical lines in Figure 2 show (i) the mean of the distribution and (ii) the movement from that point due to a stylized shock to economic insecurity, while the dotted lines indicate the percentiles at which the discrete groupings occur. The figure therefore shows that the standard deviation shock moves an individual with an average SF-36 MH score of 74.24 (see Appendix A1) around 1/9th of the distance required to place them at the 81st percentile ($1.76 / (74.24 - 59.11) \approx 1/9$) which corresponds to the percentile at which one is classified as likely having a mild mental disorder. Similar results can be seen for the 89th and 95th percentiles which serve as indicators for moderate and severe mental disorders.¹⁶

Thus we see that for the average individual the negative health effects of economic insecurity are unlikely to greatly affect their mental health status. Indeed many shocks are required to make an otherwise healthy person mentally unwell. However this does not imply that the effects of economic insecurity are trivial, as economic risks are widespread across the Australian population. For example only 13% of the relevant subset of our sample agree that (i) their job is secure, (ii) they are comfortable with their financial position, and (iii) that they could easily raise emergency funds amounting to 2-3 weeks of the average weekly household income. Consequently it is likely that most individuals face some sense of economic insecurity and experience slightly diminished mental wellbeing as a result. Thus it is necessary to consider the rate of exposure as well as the sensitivity to risk when evaluating the aggregate impact upon population health.

¹⁶The SF-36 requires 4.7 additional shocks to span the mild disorder threshold and 5.0 to reach the point of severe impairment.

Using this idea, we are able to model the sensitivity of the morbidity rate of mental illness to the overall level of economic insecurity. From the estimated density, we observe that approximately 3.5% of the Australian population lie 1.76 units below the cutoff for a minor mental disorder. A standard deviation shock to all individuals would therefore be expected to increase the morbidity rate of those with at least some mental disorder by this amount. If the true effect is as low as 1.4 (the lower bound on our cluster of instrumented estimates), the increase in morbidity is 2.5%, while an effect of 2 SF-36 units per standard deviation shock (the upper bound) would increase the morbidity rate by about 3.8%. These percentages are taken relative to the total population; if we consider the change relative to the current morbidity rates then a population wide shock of a single standard deviation would increase the rates by between 11-16%. Hence events that increase the insecurity of the entire population such as business cycles, changes in labor market regulations, or cuts to social safety nets are likely to have substantial negative consequences for public health.

7 Conclusion

This paper has investigated the extent to which economic insecurity causes deterioration in the mental health of the Australian public. A variety of economic insecurity measures were developed and examined as determinants of mental health as measured by the SF-36 summary index. Coefficient estimates on a number of insecurity estimates were significant, robust, of the expected sign and passed a variety of diagnostic tests. Results indicate that negative health effects can be attributed to exogenous changes in financial dissatisfaction, feelings of job insecurity, the inability to produce emergency funds, the risk of downward income mobility and the probability of failing to meet standard household expenses in the future. Our preferred models indicate that a standard deviation shock to the measures reduces the SF-36 Mental Summary by around 1.4-2 points. These shifts are of a plausible magnitude relative to the underlying distributions and are around 1/7th to 1/10th of the size of a shock required to move an average individual to the threshold of a minor psychological disorder.

The results represent a number of new contributions to the literature. First, ours is one of a limited number of papers to consider endogeneity issues when modeling economic risks and mental health, and our combination of instrumental variables with fixed effects models allowed us to control for endogeneity extremely thoroughly. Secondly as we employed multiple measures of insecurity we were able to ascertain whether any ill effects were specific to particular risks, or if diminished psychological health is likely to be an effect of any generic

economic risk. The consistency in statistical significance and the reasonable degree of similarity of these estimates shows that there are mental health consequences for a wide variety of objective and perceived economic risks, which reinforces the hypothesis that the common element of prospective economic loss is likely to be harmful for mental health.

References

- Abramson, I. (1982). “On bandwidth variation in kernel estimates: a square root law” *The Annals of Statistics*, 10, 1217-1223.
- Andrews, G. and Slade, T. (2001). “Interpreting scores on the Kessler Psychological Distress Scale (K10)” *Australian and New Zealand Journal of Public Health*, 25, 494-497.
- Bandyopadhyay, S. and Cowell, F. (2007). “Modelling vulnerability in the UK” LSE STICERD Research Paper 89.
- Barnes, M. and Smith, T. (2009). “Tobacco Use as Response to Economic Insecurity: Evidence from the National Longitudinal Survey of Youth” *The B.E. Journal of Economic Analysis & Policy*, 9, 1.
- Barslund, M. Chiconela, J. Rand, J. and Tarp, F. (2007). “Understanding Victimization: The Case of Mozambique” *World Development*, 35, 7.
- Blakely, T. Collings, S. and Atkinson, J. (2003). “Unemployment and suicide. Evidence for a causal association?” *Journal of Epidemiology and Community Health*, 57, 594-600.
- Bossert, W. and D’Ambrosio, C. (2013). “Measuring Economic Insecurity” *International Economic Review*, 54, 3, 1017-1030.
- Bowling A. (1997). “Measuring Health: A Review of Quality of Life Measurement Scales” London: Open University Press.
- Bucks, B. (2011). “Economic Vulnerability in the United States: Measurement and Trends” Paper Prepared for the IARIW-OECD Conference on Economic Insecurity, Paris, France.
- Buhmann, B. Rainwater, L. Schmauss, 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, 115-1142.
- Calvo, C. and Dercon, S. (2005). “Measuring individual vulnerability” Economics Series Working Papers 229, University of Oxford, Department of Economics.
- Cannuscio, C. Alley, D. Pagán, J. Soldo, E. Krasny, S. Shardell, M. Asch, D. and Lipman, T. (2012). “Housing Strain, Mortgage Foreclosure, and Health” *Nursing Outlook*, 60, 134-142.
- Caroli, E. and Godard, M. (2013). “Does Job Insecurity Deteriorate Health? A Causal Approach for Europe” PSE Working Papers hal-00784777, HAL.
- Cheng, Y. Chen, C.W. Chen, C.J. and Chiang T. (2005). “Job insecurity and its association with health among employees in the Taiwanese general population” *Social Science & Medicine*, 61, 41-52.

- Cragg, J. and Donald, S. (1993). "Testing Identifiability and Specification in Instrumental Variables Models" *Econometric Theory*, 9, 222-240.
- De Witte, H. (1999). "Job insecurity and psychological well-being: Review of the literature and exploration of some unresolved issues" *European Journal of Work and Organizational Psychology*, 8, 155-177.
- Dominitz, J. and Manski, C. (1997). "Perceptions of Economic Insecurity" *Public Opinion Quarterly* 61, 2, 261-87.
- Donaldson, D. and Weymark, J. (1980). "A Single-Parameter Generalization of the Gini Indices of Inequality" *Journal of Economic Theory*, 22, 67-86.
- Ferrie J. (2001). "Is job insecurity harmful to health?" *Journal of the Royal Society of Medicine*, 94, 71-76.
- Ferrie J. Shipley, M. Marmot, M. Stansfeld, S. and Davey Smith, G. (1998a). "The health effects of major organisational change and job insecurity" *Social Science & Medicine*, 46, 243-254.
- Ferrie J. Shipley, M. Marmot, M. Stansfeld, S. and Davey Smith, G. (1998b). "An uncertain future: the health effects of threats to employment security in white collar men and women" *American Journal of Public Health*, 88, 1030-1036.
- Fryer, D. and Fagan, R. (2003). "Toward a critical community psychological perspective on unemployment and mental health research" *American Journal of Community Psychology*, 32, 89-96.
- Green, F. (2011). "Unpacking the misery multiplier: How employability modifies the impacts of unemployment and job insecurity on life satisfaction and mental health" *Journal of health economics*, 30, 265-276.
- 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.
- Hansen, L. (1982). "Large Sample Properties of Generalized Method of Moments Estimators," *Econometrica*, 50, 1029-1054.
- Hausman, J. (1978). "Specification Tests in Econometrics". *Econometrica*, 46, 6, 1251-1271.
- Hintikka, J. Saarinen, P. and Viinamaki, H. (1999). "Suicide mortality in Finland during an economic cycle 1985-1995" *Scandinavian Journal of Public Health*, 27, 85-88.
- Kahneman, D. and Tversky, A. (1979). "Prospect Theory: An Analysis of Decision under Risk", *Econometrica*, 47, 2, 263-291.
- Kalleberg, A. (2009). "Precarious Work, Insecure Workers: Employment Relations in Transition" *American Sociological Review*, 74, 1-22.
- Kessler, R. Andrews, G. and Colpe, L. (2002). "Short screening scales to monitor population prevalences and trends in non-specific psychological distress" *Psychological Medicine*, 32, 959-956.
- Kessler, R. Turner, J. and House, J. (1989). "Unemployment, reemployment, and emotional functioning in a community sample" *American Sociological Review*, 54, 648-657.
- Kleibergen, F. and Paap, R. (2006). "Generalized Reduced Rank Tests Using the Singular Value Decomposition" *Journal of Econometrics*, 133, 97-126.

- Landsbergis, P. Grzywacz, J. and LaMontagne, A. (2012). “Work organisation, job insecurity and occupational health disparities” *American journal of industrial medicine*, 1–21. doi: 10.1002/ajim.22126.
- Larson, J. Wilson, S. and Beley, R. (1994). “The Impact of Job Insecurity on Marital and Family Relationships.” *Family Relations*, 43, 138–143.
- Laszlo, K. Pikhart, H. Kopp, M. Bobak, M. Pajak, A. and Malyutina, S. (2010). “Job insecurity and health: a study of 16 European countries” *Social Science & Medicine*, 70, 6, 867–874.
- Leamer, E. (1983). “Let’s Take the Con Out of Econometrics” *American Economic Review*, 73, 31–43.
- Lim, V. (1996). “Job insecurity and its outcomes: Moderating effects of work-based and nonwork-based social support” *Human Relations*, 2, 171–194.
- Luechinger, S. Meier, S. and Stutzer, A. (2009). “Why Does Unemployment Hurt the Employed? Evidence from the Life Satisfaction Gap between the Public and the Private Sector” *Journal of Human Resources*, 45, 4, 998–1045.
- McDonough, P. (2000). “Job insecurity and health” *International Journal of Health Services*, 30, 453–476.
- Meltzer, H. Bebbington, P. Brugha, T. Jenkins, R. McManus, S. and Stansfeld S. (2009). “Job insecurity, socio-economic circumstances and depression” *Psychological Medicine*, 40, 8, 1401–7.
- Mirowsky, J. and Ross, C. (1989). “Social Causes of Psychological Distress” Aldine De Gruyter, New York.
- Nadaraya, E. (1964). “On Estimating Regression”. *Theory of Probability and its Applications*, 9, 1, 141–2.
- Nichols, A. and Rehm, P. (2014). “Trends in Income Inequality, Intertemporal Variability, and Mobility Risk in Thirty Countries” *Review of Income and Wealth*, S60, 98–116.
- OECD (2004). “More and Better Jobs? Aggregate Performance during the Past Decade” OECD, vol. Employment Outlook, Chap. 1.
- Offer, A. Pechey, R. and Ulijaszek, S. (2010). “Obesity under affluence varies by welfare regimes: The effect of fast food, insecurity, and inequality” *Economics and Human Biology*, 8, 3, 297–208.
- Osberg, L. (1998). “Economic Insecurity” Discussion Papers 0088, University of New South Wales, Social Policy Research Centre.
- Osberg, L. and Sharpe, A. (2002). “An Index of Economic Well-Being for Selected OECD Countries” *Review of Income and Wealth*, 48, 3, 291–316.
- Raviv, A. Keinan, G. Abazon, Y. and Raviv, A. (1990). “Moving as a stressful life event for adolescents” *Journal of Community Psychology*, 18, 130–140.
- Rohde, N. Tang, K. and Rao, D. (2014). “Distributional Characteristics of Income Insecurity in the US, Germany and Britain” *Review of Income and Wealth*, S60, 159–176.
- Schaffer, M. (2010). “xtivreg2: Stata module to perform extended IV/2SLS, GMM and AC/HAC, LIML and k-class regression for panel data models” <http://ideas.repec.org/c/boc/bocode/s456501.htm>.
- Scheve, K. and Slaughter, M. (2004). “Economic insecurity and the globalization of production” *American Journal of Political Science* 48, 4, 662–674.
- Schuster, E. (1985). “Incorporating support constraints into nonparametric estimators of densities” *Communications in Statistics*, 14, 1123–1136.

- Sharpe, A. and Osberg, L. (2009). “New Estimates of the Index of Economic Well-being for Selected OECD Countries, 1981 – 2007” CSLS Research Reports 2009-11, Centre for the Study of Living Standards.
- Slopen, N. Glynn, R. Buring, J. Lewis, T. Williams, D. and Albert, M. (2012). “Job strain, job insecurity, and incident cardiovascular disease in the Women’s Health Study: results from a 10-year prospective study” *PloS One* 7:e40512.
- Smith, T. Stoddard, C. and Barnes, M. (2009). “Why the poor get fat: Weight gain and economic insecurity” *Forum for Health Economics & Policy*, 12, 5.
- Standing, G. (1997). “Globalisation, labour flexibility and insecurity: The era of market regulation” *European Journal of Industrial Relations*, 3, 1, 7-38.
- Stiglitz, J. Sen, A. and Fitoussi, J. (2009). Report by the commission on the measurement of economic performance and social progress. Paris. <http://www.stiglitzsen-fitoussi.fr/en/index.htm>.
- Stuckler, D. Basu, S. Suhrcke, M. Coutts, A. and McKee, M. (2009). “The public health effect of economic crises and alternative policy responses in Europe: an empirical analysis” *The Lancet*, 374, 315-323.
- Sverke, M. Hellgren, J. and Näswall, K. (2002). “No security: A meta-analysis and review of job insecurity and its consequences,” *Journal of Occupational Health Psychology*, 7, 3, 242-264.
- Tsutsumi, A. Kayaba, K. Theorell, T. and Siegrist, J. (2001). “Association between job stress and depression among Japanese employees threatened by job loss in a comparison between two complementary job-stress models” *Scandinavian Journal of Work, Environment and Health*, 27, 2, 146–153.
- United Nations Department of Economic and Social Affairs (2008). World Economic and Social Survey 2008: Overcoming Economic Insecurity, UNDESA.
- Ware, J. Snow, K. Kosinski, M. and Gandek, B. (2000). “SF-36 Health Survey: Manual and Interpretation Guide” QualityMetric Inc., Lincoln, RI.
- Watson, G. (1964). “Smooth regression analysis” *Sankhya*, 26, 15 175–184.
- Western, B. Bloom, D. Sosnaud, B. and Tach, L. (2012). “Economic insecurity and social stratification” *Annual Review of Sociology*, 38 , 341–359.
- Weymark, J. (1981). “Generalized Gini Inequality Indices,” *Mathematical Social Sciences*, 1, 409–430.
- White, H. and X. Lu (2010). “Robustness checks and robustness tests in applied economics” UCSD Department of Economics discussion paper.
- Wu, D. (1973). “Alternative Tests of Independence between Stochastic Regressors and Disturbances” *Econometrica*, 41, 4, 733–750.

8 Appendix

A1. Data Description

This section provides additional descriptive information on the variables used in the paper. Table 3 summarizes the mental health variable and insecurity scores; Table 4 gives the instruments and Table 5 summarizes the control variables used in the regression models.

Table 3: Data Descriptive Statistics - Mental Health and Insecurity Scores (Appendix A1)

Variable	Mean	Standard Deviation	Range	Total Obs	Missing Waves
SF-36	74.24	17.06	0-100	132,063	-
Job Insecurity	3.007	1.698	1-7	82,174	-
Financial Dissatisfaction	3.624	2.298	0-10	147,671	-
Emergency Funds	1.788	1.061	1-4	130,720	-
Income Drop	0.080	0.272	0-1	283,707	1
L&C Index	-32621	94045	$(-\infty, +\infty)$	113,915	1,2,3
P - Unemployment	0.018	0.026	$[0, 1]$	71,172	11
P - Income Drop	0.126	0.091	$[0, 1]$	39,007	11
P - Exp Distress	0.024	0.080	$[0, 1]$	56,249	9,10,11

Note: All estimates are based on the full sample pooled across waves. We use the notation A-B to define a range occupied by natural numbers (i.e. integers) while a continuous interval is given in square brackets to denote a closed interval and curved brackets for an open interval (e.g. $[0, 1]$ denotes the real line from 0 to 1 inclusive).

Table 4: Data Descriptive Statistics - Instruments (Appendix A1)

Variable	Mean	Standard Deviation	Brackets	Total Obs	Missing Waves
Unemployment by Education Level	0.056	0.030	10	157397	-
Job Insecurity by Age Group	3.057	0.377	16	147823	-
Financial Dissatisfaction by Region	3.626	0.201	13	201338	-

Note: All estimates are based on the full sample pooled across waves. The third column gives the number of brackets over which the localized average is taken.

Table 5: Data Descriptive Statistics - Control Variables (Appendix A1)

Variable	Mean	Standard Deviation	Range	Total Obs	Missing Waves
Age	35.70	22.32	$0 - \infty$	201,342	-
Income	44,744	30094	$0 - \infty$	201,342	-
Education	12.95	2.077	10-18	147,823	-
H-hold Size	3.273	1.592	1-14	201,342	-
Remoteness	0.551	0.798	0-4	201,336	-
Gender	0.512	0.499	0-1	201,342	-
Marital Status	0.491	0.502	0-1	147,778	-
Social Satisfaction	4.591	1.659	1-7	131,308	-
General Health	83.22	23.27	0-100	130,736	-
Became Married	0.025	0.157	0-1	118,434	1
Became Separated	0.040	0.197	0-1	118,105	1
Pregnant	0.053	0.225	0-1	118,174	1
Birth	0.037	0.185	0-1	118,043	1
Death Relative	0.112	0.316	0-1	118,178	1
Victim Violence	0.017	0.129	0-1	118,051	1

Note: All estimates are based on the full sample pooled across waves. Gender refers to the proportion of females while marital status gives the proportion married.

A2. Distribution plots for insecurity indices

Density plots of the distributions of each insecurity index are given below. Discrete indices are plotted in

Figure 3 using bar charts while continuous indices are depicted with adaptive kernel density estimates in Figure 4.

Figure 3: Distributional Graphs - Discrete Insecurity Indices (Appendix A2)

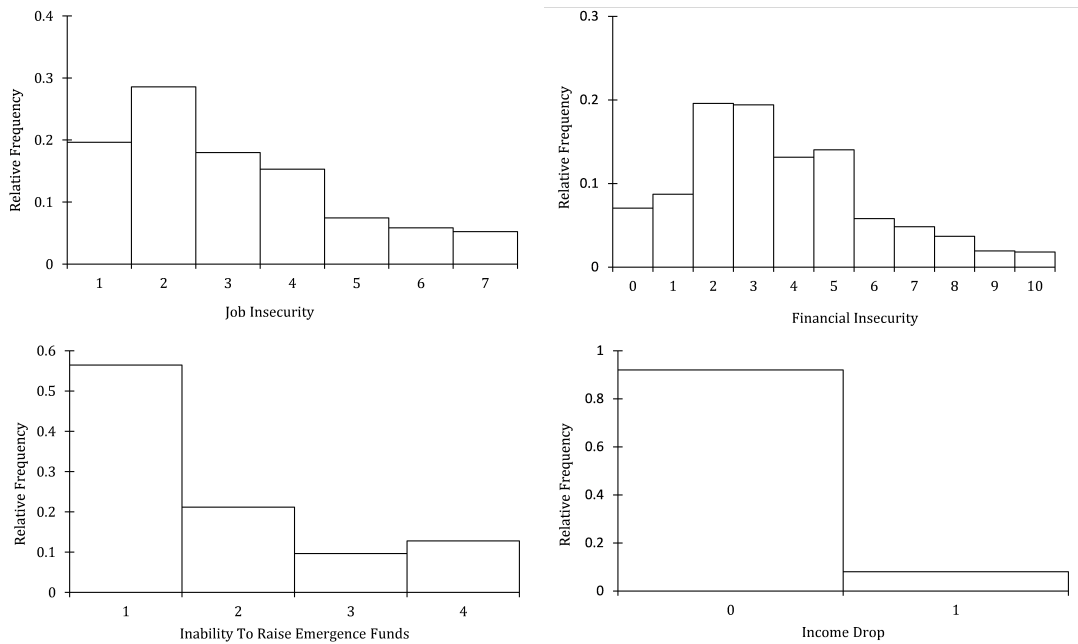
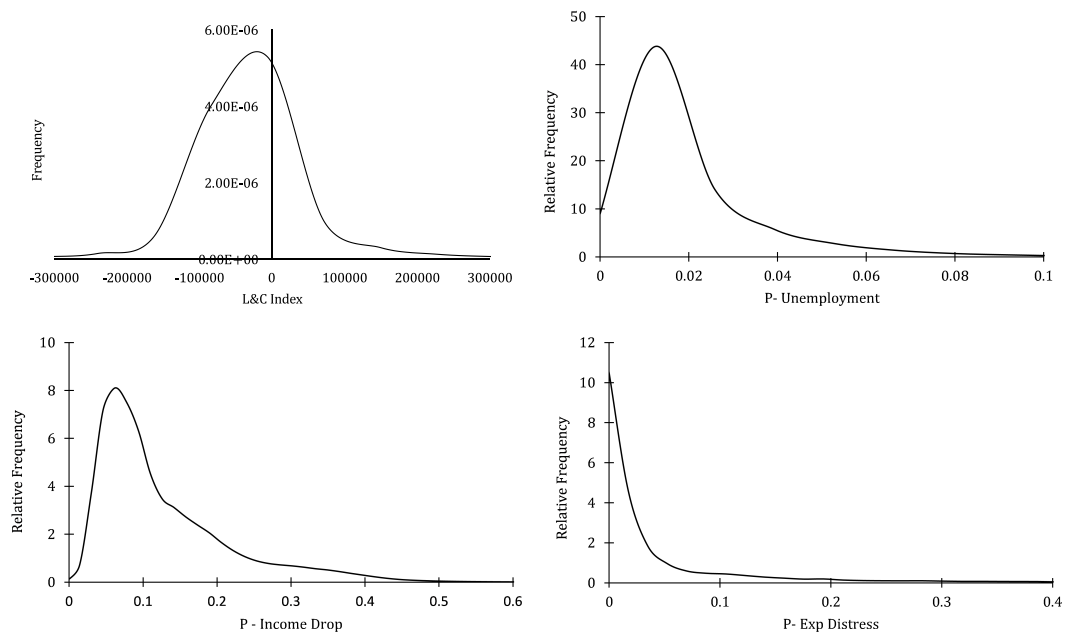


Figure 4: Distributional Graphs - Continuous Insecurity Indices (Appendix A2)



A3. Correlations between insecurity measures

To investigate relationships between the various insecurity scores we report the matrix $\hat{\Omega}$ describing the pairwise correlations between the measures. Estimates are based on an intersect of 17,201 person-years.

Table 6: Pooled Correlations Between Insecurity Measures (Appendix A3)

	Mental Health			Economic Insecurity Score					
	SF-36	EI^1	EI^2	EI^3	EI^4	EI^5	EI^6	EI^7	EI^8
Job Insecurity	-0.207	1							
Financial Dissatisfaction	-0.278	0.252	1						
Emergency Funds	-0.201	0.168	0.340	1					
Income Drop	-0.030	0.043	0.095	0.066	1				
L&C Index	-0.043	0.060	0.128	0.098	0.566	1			
P - Unemployment	-0.187	0.486	0.338	0.380	0.176	0.189	1		
P - Income Drop	-0.095	0.223	0.266	0.122	0.710	0.270	0.245	1	
P - Exp Distress	-0.188	0.126	0.361	0.324	0.121	0.103	0.240	0.190	1

Note: The first two columns give the correlations between the two mental health measures and the insecurity indices. The next eight columns/rows give the pairwise correlations between insecurity indices. All estimates are based on the pooled sample.

Table 6 illustrates that *all* insecurity measures have the expected correlations with mental health. In most cases the correlations are fairly strong, especially for the survey based insecurity measures in the first three rows. We also observe that all insecurity scores are positively correlated with each other in a total of 28 pairwise comparisons.

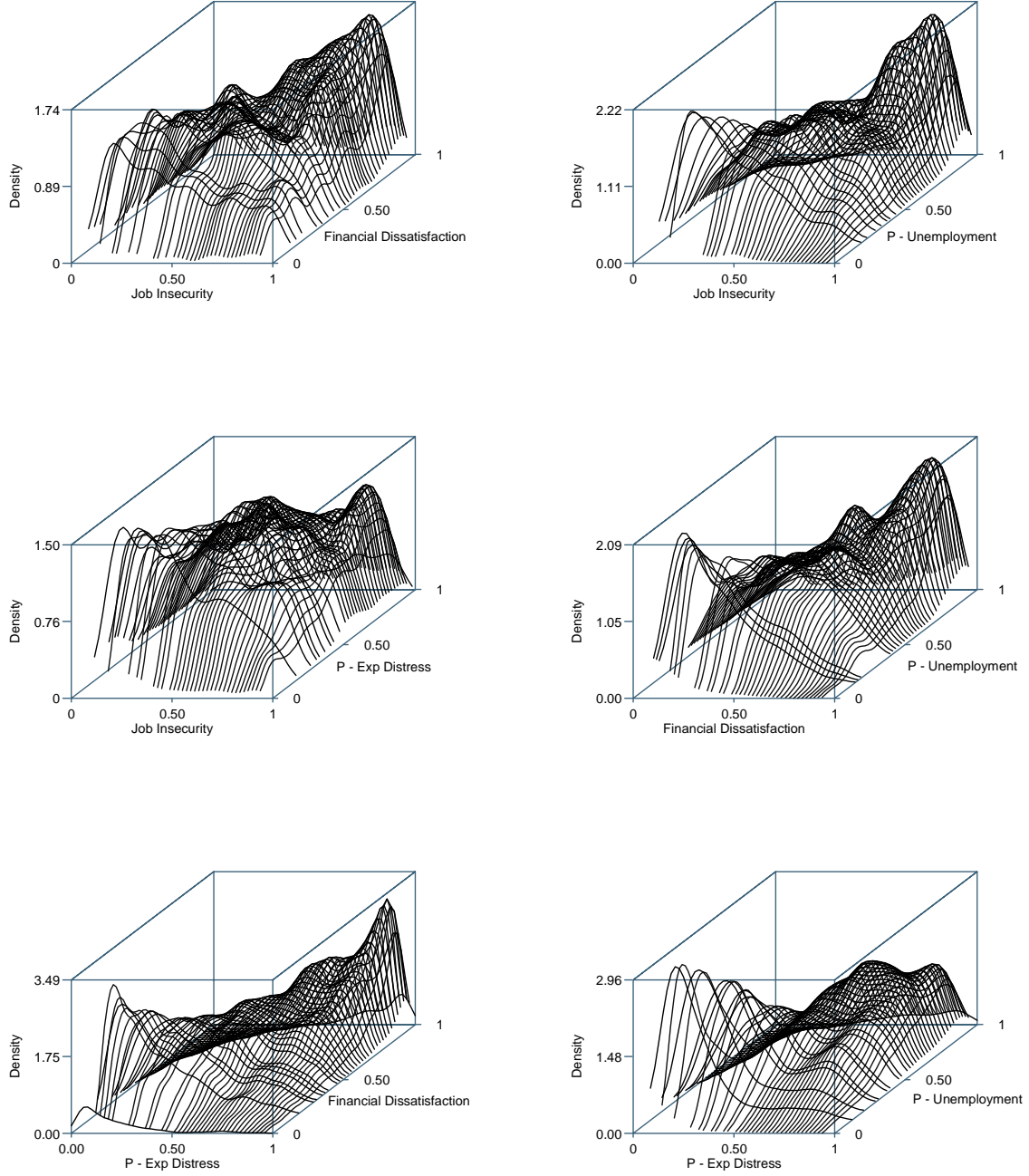
Further light can be shed on the relationships between the indices by plotting their joint distributions. This is done for the selected measures from Figure 1. We take the *between* individual variation captured as $\bar{EI}_i^j = \frac{1}{T} \sum_{t=1}^T EI_{it}^j$ for measure j and order the observations $\bar{EI}_1^j < \bar{EI}_2^j < \dots < \bar{EI}_n^j$. We then define

$$\gamma_{i^*}^j = \begin{cases} 1 & \text{if } \bar{EI}_{i^*}^j < \bar{EI}_i^j \\ 0 & \text{if } \bar{EI}_{i^*}^j > \bar{EI}_i^j \end{cases} \quad i = 1 \dots n \quad (7)$$

$$\hat{F}_i^j(\bar{EI}_i^j) = \frac{1}{n} \sum_{i^*=1}^n \gamma_{i^*}^j \quad (8)$$

where $\hat{F}_i^j(\bar{EI}_i^j)$ is the empirical CDF based upon the rank transformed data. Plotting $\hat{F}_i^j(\bar{EI}_i^j)$ against $\hat{F}_i^k(\bar{EI}_i^k)$ thus gives a copula style PDF on $[0, 1]^2$ which neatly controls for the distributional differences between j and k . The densities are fitted using a bivariate kernel where the bandwidth matrix is selected on the basis of minimizing the Mean Squared Integrated Error of an implicit Gaussian. The pairwise plots of the selected indices are given below.

Figure 5: Bivariate Kernel Density Plots: Rank Transformations of Selected Indices (Appendix A3)



Note: Each vertical axis gives the estimates frequency $\hat{f}(F^j, F^k)$ while the horizontal axes give the rank normalized insecurity measures.

Figure 6 shows that probability density seems to congregate both around the origin (0,0) and the far corner

of the unit square (1,1). This shows that individuals who were judged to be highly insecure on one measure were disproportionately likely to score highly on another, while the same holds for those with low insecurity scores. Nevertheless there is a considerable degree of variation in each of the plots.

A4. Robustness checks

This section provides robustness checks for the main estimations presented in Tables 1 and 2. Equations are subjected to re-specification according to the predefined set of peripheral variables (giving 16 auxiliary estimates for each reported coefficient). Table 7 gives the parameter estimates (also reported in Table 1), the smallest and largest auxiliary estimates, the mean, standard deviation and averaged z statistics of the auxiliary estimates and the proportion of estimates that are negative and positive.

Table 7: Robustness Checks of Economic Insecurity on M (Appendix A4)

Variable	$\hat{\phi}_{FE}^j$	Ave z	% $\pm 2\sigma$	% < 0	% > 0	$\hat{\phi}_{IV}^j$	Mean	Ave z	% $\pm 2\sigma$	% < 0	% > 0
Job Insecurity	-0.710	-17.72	100	100	0	-0.866	-0.991	-2.000	100	100	0
Financial Dissat	-0.788	-27.58	100	100	0	-0.522*	-0.563	-2.055	100	100	0
Emergency Funds	-1.182	-17.19	100	100	0	-1.282	-1.290	-2.382	100	100	0
Income Drop	-0.438	-2.654	100	100	0	-7.132	-7.194	-3.037	100	100	0
L&C Index	8.0E-07	0.288	75	25	75	2.4E-6	2.92E-6	1.877	100	25	75
P - Unemployment	-42.71	-7.655	100	100	0	-82.66	-85.55	-1.697	100	100	0
P - Income Drop	-5.423	-5.631	100	100	0	-3.877	-4.659	-2.250	100	100	0
P - Exp Distress	-13.02	-10.50	100	100	0	-20.79	-31.38	-1.108	100	100	0

The first column gives ϕ^j estimated in the fixed effects model with the use of instruments. The second column gives the standard error of the coefficient while the third and fourth columns show the lowest and highest estimates for ϕ^j from the 16 auxiliary regressions. The fifth column gives the mean of the auxiliary estimates and the sixth their average z statistic. The last three columns give the proportion of auxiliary estimates within two standard deviations of the original, the proportion that are negative and the proportion that are positive.

Results from Table 7 indicate that the parameter estimates are quite robust to changes in the peripheral variables. In all but two instances the original estimates lie close to the means obtained from the auxiliary estimates and in no instances did the signs switch from negative to positive (or vice versa). It should be noted however that if the set of peripheral variables was extended to include the life event indicators (such as births, marriages, deaths etc) this would introduce a greater degree of variation than evident in Table 7. However as these variables are likely to have strong causal effects on mental wellbeing, are generally highly significant and are of the expected signs, they retained across all models.