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Does poverty reduce mental health? An instrumental variable analysis

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ABSTRACT

That poverty and mental health are negatively associated in developing countries is well known among epidemiologists. Whether the relationship is causal or associational, however, remains an open question. This paper aims to estimate the causal effect of poverty on mental health by exploiting a natural experiment induced by weather variability across 440 districts in Indonesia ($N = 577{,}548$). Precipitation anomaly in two climatological seasons is used as an instrument for poverty status, which is measured using per capita household consumption expenditure. Results of an instrumental variable estimation suggest that poverty causes poor mental health: halving one's consumption expenditure raises the probability of suffering mental illness by 0.06 point; in terms of elasticity, a 1% decrease in consumption brings about 0.62% more symptoms of common mental disorders. This poverty effect is approximately five times stronger than that obtained prior to instrumenting and is robust to alternative distributional assumption, model specification, sample stratification and estimation technique. An individual's mental health is also negatively correlated with district income inequality, suggesting that income distribution may have a significant influence upon mental health over and above the effect of poverty. The findings imply that mental health can be improved not only by influencing individuals' health knowledge and behaviour but also by implementing a more equitable economic policy.

1. Introduction

The negative association between poverty and mental health in developing countries has been increasingly documented. Research from various parts of the world generally shows that low levels of income, education, and assets as well as low social class are correlated with a higher probability of having common mental disorders (Lund et al., 2010). However, empirical evidence regarding the causal effect of the association remains scarce. Few studies have investigated the strength or the direction of causality between poverty and mental health in developing countries, although such study clearly benefits the formulation of public policy aimed at improving the health of the population. In encouraging study of this topic in the United States, Stowasser et al. (2011, p.2) note that ' … if causal links between wealth and health were confirmed, society would likely benefit from more universal access to health care and redistributive economic policy. Yet, if such causal links were rebutted, resources would be better spent on influencing health knowledge, preferences, and ultimately the behavior of individuals.' Considering both the growing burden of disease attributed to mental illness (IHME, 2013) and tightly constrained health budgets (Patel, 2007), it is important to understand whether poverty reduces mental health in developing countries.

The fact that poverty is negatively associated with mental health in low- and middle-income countries is hardly surprising, but to reach a convincing estimate of its causal effect is certainly not an easy task. Two-way or simultaneous causation may come into play (Smith, 1999), inflating the estimated effect and making it impossible for researchers looking at observational data to separate the effect of wealth on mental health (social causation hypothesis) from that of the reverse (social selection hypothesis). Secondly, the observed wealth–health relationship may be confounded by unobserved common causes that accidentally induce a spurious correlation. Genetic frailty, early childhood environment, family background and preference or taste for lifestyle may impact both an individual's ability to work (and hence accumulate wealth) and his or her susceptibility to mental illness (Stowasser et al., 2011). The study on the mental health effect of poverty may also suffer from what is generally known as the attenuation bias. More often than not, wealth is measured with error, as a noisy, low signal-to-noise ratio variable which could trivially result in a downward-biased parameter estimate (Cameron and Trivedi, 2005). Because these endogeneity problems might be working at the same time, it is

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difficult to predict the magnitude and direction of the potential bias resulting from their presence *a priori*. In addition, the small number of population data available in developing countries remains a major obstacle for public health research.

The aim of this paper is therefore to address these issues. We apply instrumental variable and control function estimators to a large (N = 987,205), nationally representative dataset from Indonesia, namely the *Riset Kesehatan Dasar* (Riskesdas) 2007. We use seasonal precipitation anomaly, defined as the average deviation of monthly precipitation from its half-century (1951–2000) normals in all 440 *kabupaten* (districts) in Indonesia, as an instrument for poverty status. The identifying assumptions are that precipitation anomaly strongly predicts per capita household expenditure in a largely agricultural economy (relevance condition), is randomly assigned hence unrelated to any potential unobserved confounders (validity condition), and is exerting its influence upon mental health only through its effect on consumption expenditure (exclusion restriction). Conditional on these partially testable assumptions, the instrumental variable approach allows the analyst to isolate the exogenous variation of poverty, thus allowing for the derivation of a consistent estimate of the mental health effect of poverty in the presence of endogeneity. This study is one of the few population-based studies that attempts to look beyond the simple correlation between poverty and mental health in the context of low- and middle-income countries.

2. Poverty and mental health: association and causality

The two-way causation between poverty and mental health has been recognised for quite some time. The consensus among epidemiologists seems to suggest that the social causation hypothesis (wealth → health) is more plausible for explaining high-prevalence mental disorders such as depression and anxiety disorders, whilst the social selection hypothesis (health → wealth) is probably more relevant for low-prevalence mental disorders like schizophrenia (Goldberg and Morrison, 1963; Muntaner et al., 2004; Saraceno et al., 2005). Despite the intuitive logic behind this consensus (Adler and Ostrove, 1999; Dohrenwend et al., 1992), it is important to note that there have been only sparse empirical attempts to separate the competing causal directions (Muntaner et al., 2004).

Amid the paucity of population data equipped with reliable income and mental health measures, research in low- and middle-income countries have so far been able to investigate only the associational nature between wealth and mental health. Researchers often have to rely on small community or facility samples which are not only prone to the self-selection bias but also limit the application of multivariate statistical tools. The majority of community and facility studies conducted throughout the developing world suggests that poverty is positively associated with mental illness (Lund et al., 2010). Population-based studies (Dzator, 2012; Hamad et al., 2008; Myer et al., 2008) also support this finding, although they have not yet addressed the endogeneity issues; in the Indonesian setting in particular, Tampubolon and Hanandita (2014) recently confirmed the association using data from the Indonesia Family Life Survey 2007.

In contrast to the associational nature of studies conducted in developing countries, investigations of the causal effect of wealth on mental health began to appear as early as the mid-1990s in developed countries. Acknowledging the dual relationship between health and economic status (Smith, 1999) as well as the potential error in measuring income and the possibility of confounding due to unmeasured variables, Ettner (1996) took a set of variables (work experience, state-wide unemployment rate, parental education, spousal and spouse's parents' education, and spousal work experience) as instruments for individual income in the United States ($N = 8000$). She applied a two-stage instrumental variable estimator and found that reduced income leads to worse mental health (as indicated by higher Center for Epidemiologic Studies Depression Scale (CES-D) scores). The effect was four times stronger after instrumenting for income, although Meer et al. (2003) and Frijters et al. (2005) later cast doubt on the validity of her instrument set. Using the same identification strategy but with a different instrument set (age, inheritance, time in current job, mother's education, fraction of household income earned by the respondent, hours watching TV and rural-urban residence), Zimmerman and Katon (2005) did not detect any statistically significant effect of financial status (debt-to-asset ratio) on mental health (CES-D score). They admitted that the non-significance might be due to the poorly performing instrument set, although one could argue that the application of an instrumental variable estimator to a small sample ($N = 2000$) might well account for the finding.

Three points in the existing literature are worth noting. First, the negative association between poverty and mental health is generally found in both developed and developing countries, but there is a marked difference with respect to the weight of the evidence. Among the studies conducted in low- and middle-income countries, there has been a lack of the investigation into the causal relationship that has been performed in high-income countries. Perhaps the only study that has sought to do so is the one conducted by Chin (2010), which did not find a statistically significant income effect on mental health in Malawi ($F = 10.34$; $N = 2400$). Second, although the small-sample bias as well as the inefficiency properties of instrumental variable estimator have been well studied (Bound et al., 1995; Cameron and Trivedi, 2005), previous applications were mostly limited to small datasets; sometimes, in addition, they were carried out with a rather weak instrument set. Finally, instrumental variable analysis offers a way to address endogeneity problems, but due to the limited availability of data collected in developing countries, it is likely that researchers would not have the privilege of exploring instrument sets like those used in the two US studies reviewed above. This does *not* mean, however, that there is no way for researchers working with data from developing countries to implement the technique.

3. Weather variability as a source of exogenous variation

One promising instrument for individual income to be used in developing countries is the variability of rainfall over time and across places. It is not difficult to see that, in predominantly agriculture-dependent economies, the amount of precipitation in a given locality should be positively correlated with crop production, hence strongly determining individual income or consumption expenditure. Levine and Yang (2006, p.5) showed that 'higher local rainfall leads to higher rice output in Indonesian districts' which 'occurs contemporaneously (in the same calendar year), rather than with a lag', although the effect seems to be statistically significant only 'in districts that are not major cities'. This is also supported by Kishore et al. (2000), who looked at the impact of rainfall anomalies during the 1997–1998 El Niño event in Indonesia. In Africa, analysis conducted using Ugandan data has also resulted in similar findings: higher rainfall is correlated with higher production of coffee, bananas and peas as well as higher GDP (Björkman-Nyqvist, 2013). In fact, Miguel et al. (2004) found that positive rainfall shock is generally associated with positive GDP growth in 41 African countries. At the individual level, the positive correlation between rainfall shock and individual income has been confirmed in the Philippines (Yang and Choi, 2007), Malawi (Chin, 2010), Tanzania (Savage and Fichera, 2013) and Thailand (Paxson, 1992) as well. Studies consistently show that positive rainfall shock can be generally interpreted as a positive exogenous income shock for individuals living in developing countries.

Working under the assumption that rainfall shock is a random variate uncorrelated with any unobserved common causes and is exerting its influence on the health outcome of interest only through its effect on the instrumented variable, researchers have been able to estimate the causal effect of individual economic status on general health status and subjective well-being in Malawi (Chin, 2010) as well as on body mass index, self-rated health, height-for-age, weight-for-age and vaccination coverage in Tanzania (Savage and Fichera, 2013). In the Philippines, Glewwe and King (2001) used rainfall shock in combination with the price of salt to identify the impact of early childhood nutritional status on cognitive development. These demonstrate the utility of weather variability as a natural experiment.

In the next section we describe the data, measures and statistical methods used to estimate the causal effect of poverty on mental health in Indonesia.

4. Methods

4.1. Data

The data is drawn from the *Riset Kesehatan Dasar* (Riskesdas) 2007. Managed by the Ministry of Health of the Republic of Indonesia, the Riskesdas study is the largest public health study ever conducted in the country. The 2007 wave includes 987,205 individuals from 258,366 households residing in all 440 districts and is representative of the Indonesian population (Kemenkes, 2008). Its size and coverage clearly distinguish the Riskesdas dataset from the Indonesia Family Life Survey (IFLS) dataset (30,000 individuals living in 260 districts) that was previously analysed by Tampubolon and Hanandita (2014, see also online appendix). Informed consent was obtained prior to interview, and participants' confidentiality was strictly protected. Further details regarding ethical and sampling procedures are available in Kemenkes (2008). For our purposes, individuals younger than 15 years old were excluded from the analysis because of their ineligibility for the mental health questionnaire (Kemenkes, 2008); also excluded were those who reported a history of schizophrenia. These exclusions yield a complete-case final sample size of 577,548 individuals.

4.2. Measure of mental health

Mental health is measured using the 20-item Self-Reporting Questionnaire (SRQ-20), which was specifically developed as an instrument for detecting non-psychotic mental disorders in primary health care settings (Harding et al., 1980). The instrument has favourable psychometric properties and has been validated in many developing countries including Vietnam, Rwanda, Mongolia, China and others (Beusenberg and Orley, 1994; Chen et al., 2009; Ghubash et al., 2001; Giang et al., 2006; Pollock et al., 2006; Scazufca et al., 2009; Scholte et al., 2011; Stratton et al., 2013). In the Riskesdas 2007 study, eligible respondents were asked to report whether or not they experienced the 20 symptoms of non-psychotic mental disturbances (exact wording is provided in online appendix). Responses were coded using a binary 'yes/no' indicator, and mental health scores were derived by summing the individual items. This yields a mental health score whose theoretical value ranges from 0 (mentally healthy) to 20 (severely depressed). In accordance with a validation study conducted by Ganihartono (1996), a cut-off point of 6 is used. Therefore, individuals are classified as having clinically significant symptoms of common mental disorders (probable caseness) if their mental health scores are equal to or higher than six. Both the raw and dichotomised mental health scores are analysed in the following statistical analysis.

4.3. Measure of poverty

Poverty is measured using the log-transformed per capita household consumption expenditure, which reflects 'a household's ability to meet (or exceed) their material needs and to access services' (Howe et al., 2012, p.876). This measure is relatively accurate for measuring standards of living in Indonesia because of its ability to capture the monetary welfare of the self-employed or informal workers (Deaton and Zaidi, 2002) who constitute the majority (60–70%) of the Indonesian labour force (Nazara, 2010). Household expenditure is insensitive to intermittent income shock; it is thus capable of delivering a good approximation for permanent income (Deaton and Zaidi, 2002; see also Cutler and Katz, 1992; Poterba, 1989 on why expenditure is preferred to income). Substantively, as demonstrated by Ecob and Smith (1999), the log transformation allows analysts to capture the log-linear or the proportional relationship between individual poverty level and (mental) health. The transformation also makes the distribution more symmetric, hence reducing the influence of outliers.

4.4. Measure of weather variability

We use precipitation anomaly to instrument for the endogenous poverty variable. Precipitation anomaly data is obtained from the Global Precipitation and Climatology Centre (GPCC) (Schneider et al., 2014), which is operated by the German Meteorological Service (DWD). The specific dataset used in this paper is the GPCC Land–Surface Full Data Reanalysis Version 6 dataset at 0.5° resolution (Meyer-Christoffer et al., 2011; Schneider et al., 2011). The 0.5° latitude by 0.5° longitude spatial grid is approximately equal to an area of 55 $\times$ 55 km at the equator, exactly where Indonesia is located. We then matched the centroid of every district in Indonesia to its corresponding grid in order to obtain the measure of precipitation anomaly (millimetre/month) in four climatological seasons (December–January–February (DJF or winter), March–April–May (MAM or spring), June–July–August (JJA or summer) and September–October–November (SON or autumn)) for the year 2007. This is depicted in Fig. 1.

4.5. Control variables

In the models we include standard individual- and household-level socio-demographic controls, measures of health-related behaviours and two district-level contextual variables. Age is treated as a categorical variable with six factors (the reference is 15–24 years old). Gender is a dummy variable representing the female gender. Marital status is treated as a categorical variable with being married as the reference. Education is also a categorical variable; the reference is less than middle school, which in the Indonesian context is equivalent to not having completed the nine-year compulsory education (*wajib belajar*). Employment status is a dummy variable indicating whether or not an individual is unemployed. Physical activity is treated as a dummy variable denoting those who reported less physical activity (the derivation of this measure is given in Kemenkes, 2008). Frequent smoker (smokes every day), heavy drinker (drinks $\geq$ 5 days in a week) and having chronic illness (any of the following: cardiovascular disease, diabetes, cancer, stroke or hypertension) are all entered as dummy variables. Household size is a continuous covariate, while household residential location is a dummy variable indicating those who reside in an urban area. The district-level covariates are deprivation

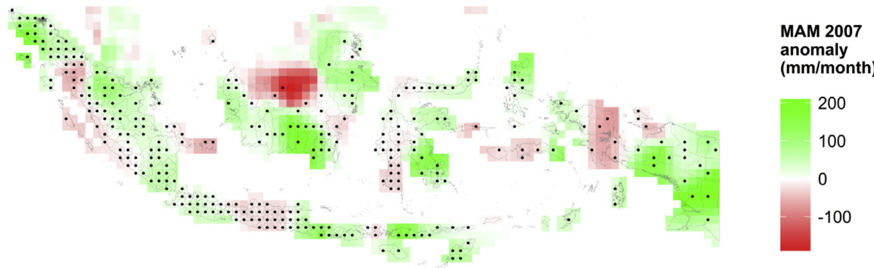

Fig. 1. Precipitation anomaly in March–April–May (MAM) 2007 season.

index and income inequality (Gini index). The deprivation index measures the lack of basic social facilities in each district (see online appendix). It was calculated from the *Potensi Desa* (Podes) 2008 dataset, which covers all 75,410 villages across the archipelago. The Gini index, in a 0-1 scale, was derived from the *Survei Sosial Ekonomi Nasional* (Susenas) 2007 dataset using the method described by Milanovic (1997). These two contextual variables are entered as continuous covariates.

4.6. Statistical method

Mental health is modelled as a function of individual-, household- and district-level determinants. We analyse both the dichotomous (probable caseness) and continuous parameterisations of the SRQ-20 score in order to avoid the loss of information due to misclassification error (Zimmerman and Katon, 2005, p.1202). Statistical analysis is carried out in two steps: initially, we treat poverty as a predetermined variable, ignoring its potential endogeneity; in the second step, we use precipitation anomaly to instrument for log per capita household consumption expenditure. Both linear and Poisson regression models are fitted for the continuous outcome, while linear probability and probit models are applied to the dichotomous outcome. The Poisson model offers a convenient way of addressing the skewed and non-negative nature of the SRQ-20 score (Gould, 2011; Nichols, 2010; Santos Silva and Tenreyro, 2006), whereas the linear model offers a number of diagnostic tools that are useful for testing the exogeneity of the suspected endogenous variable as well as for measuring the strength of the instrument set. The Generalized Method of Moments (GMM) estimator is used to estimate the endogenous linear, linear probability and Poisson models. The linear and linear probability models share an identical $E[\mathbf{z}(y-\mathbf{x}'\boldsymbol{\beta})] = \mathbf{0}$ moment condition, while the Poisson model uses the additive error $E[\mathbf{z}(y-\exp\{\mathbf{x}'\boldsymbol{\beta}\})] = \mathbf{0}$ moment condition (Windmeijer and Santos Silva, 1997). On the other hand, the endogenous probit model is fitted using the Maximum Likelihood (ML) estimator exploiting the joint normality of the correlated error terms (Cameron and Trivedi, 2010). To obtain a more intuitive interpretation of parameter estimates and to allow for a straightforward comparison with the linear probability model, we report average marginal effect instead of a raw regression coefficient for probit model.

In all cases, sampling weight is used in order to obtain nationally representative parameter estimates (Kemenkes, 2008) and standard errors are clustered by district to allow for arbitrary heteroscedasticity and autocorrelation within districts. Continuous covariates are centred to their respective grand mean (log per capita household expenditure, Gini index) or to a representative value (household size of 3, deprivation index equals 0) so that the intercept can be given a meaningful interpretation. Finally, we conduct robustness analysis in three ways: (1) we test the stability of the poverty effect by taking out some of the control variables, (2) we refit the models with urban-rural stratification, and finally (3) we re-estimate the models with a different but closely related control function estimator (Imbens and Wooldridge, 2007), as well as with a random effects estimator.

Table 1
Sample characteristics and bivariate relationships.

Variable	Summary statistics	Odds ratio
Mental health		
SRQ-20 score	2.22(3.29)	n.a
Probable caseness (SRQ-20 $\geq$ 6)	11.5%	n.a
Age		
15–24	23.0%	1.00
25–34	23.0%	1.02(0.02)
35–44	21.2%	1.14(0.02)‡
45–54	15.8%	1.41(0.03)‡
55–64	9.0%	1.95(0.06)‡
65+	8.0%	3.70(0.15)‡
Gender		
Male	48.1%	1.00
Female	51.9%	1.67(0.02)‡
Marital status		
Married	68.6%	1.00
Never Married	23.1%	0.74(0.02)‡
Divorced	1.8%	1.66(0.05)‡
Widowed	6.5%	2.63(0.06)‡
Education		
Less than middle school	53.1%	1.00
Middle school	20.3%	0.58(0.01)‡
High school	21.2%	0.49(0.02)‡
College	5.4%	0.42(0.02)‡
Employment status		
In employment or schooling	88.9%	1.00
Unemployed	11.1%	2.04(0.05)‡
Physical activity		
Adequate	70.0%	1.00
Less	30.0%	1.24(0.03)‡
Smoking behaviour		
Occasional or non-smoker	72.4%	1.00
Frequent smoker	27.6%	0.82(0.01)‡
Drinking behaviour		
Light or non-drinker	99.5%	1.00
Heavy drinker	0.5%	1.21(0.10)†
Chronic illness		
No	90.8%	1.00
Yes	9.2%	2.99(0.06)‡
Household size	4.59(1.90)	0.94(0.01)‡
Residential location		
Rural	62.5%	1.00
Urban	37.5%	0.88(0.04)†
Per capita household exp., log	12.50(0.52)	0.78(0.03)‡
District deprivation index	−0.03(1.03)	0.97(0.04)
District inequality (Gini index)	0.25(0.04)	8.15(0.75)‡
Rainfall anomaly		
March–April–May (MAM) 2007	24.82(48.67)	n.a
June–July–August (JJA) 2007	19.77(61.45)	n.a

Note: Sampling weight is not applied. *$p < 0.10$, †$p < 0.05$, ‡$p < 0.01$.

5. Results

5.1. Descriptive and bivariate analysis

Table 1 shows that the distribution of mental health scores is, as expected, extremely right skewed with 11.5% of the study participants categorised as having clinically significant symptoms of common mental disorders. This figure is very close to the official tabulation (11.6%) provided by the Ministry of Health (Kemenkes, 2008). Bivariate analysis confirms the general findings in social epidemiology. The odds of having a clinically significant mental disorder symptomatology are higher among women and among those who are old, divorced, widowed, less educated or unemployed. Individuals who reported engaging in less physical activity, suffering from chronic illness, being a heavy drinker or living in a rural area also tend to have higher odds. Reduced odds are found among those who are consumption-rich, living in an egalitarian district, and those who have a big family. That frequent smokers seem to have lower odds may somewhat counter-intuitive, but it should be noted that this may be an artefact resulting from confounding. This is formally addressed by multivariate analysis presented later.

Fig. 2 shows the spatial distribution of common mental disorders, facility deprivation, income inequality and precipitation anomaly across 440 districts in Indonesia. The hotspots appearing in the topmost panel seem to reflect the mental health costs of devastating earthquakes and tsunamis that occurred in Sumatra (Irmansyah et al., 2010) and in the islands of East Nusa Tenggara. The hotspot in central Sulawesi, however, might reflect the aftermath of the Poso conflict (Tol et al., 2010). The second panel shows the concentration of basic social facilities in Java and Bali islands, vividly portraying the consequences of the long-standing Java-centric development agenda. The third panel presents district-level income inequality with the Asmat district in Papua, the West Jakarta district in Java, and the Luwu Timur district in Sulawesi being the three most unequal districts. Finally, the last panel of Fig. 2 depicts the precipitation anomaly during the June–July–August (JJA) 2007 climatological season. Java, Maluku and some parts of southern Sumatra and central Papua were drier than the normal years, whereas Kalimantan, Sulawesi, Halmahera and the

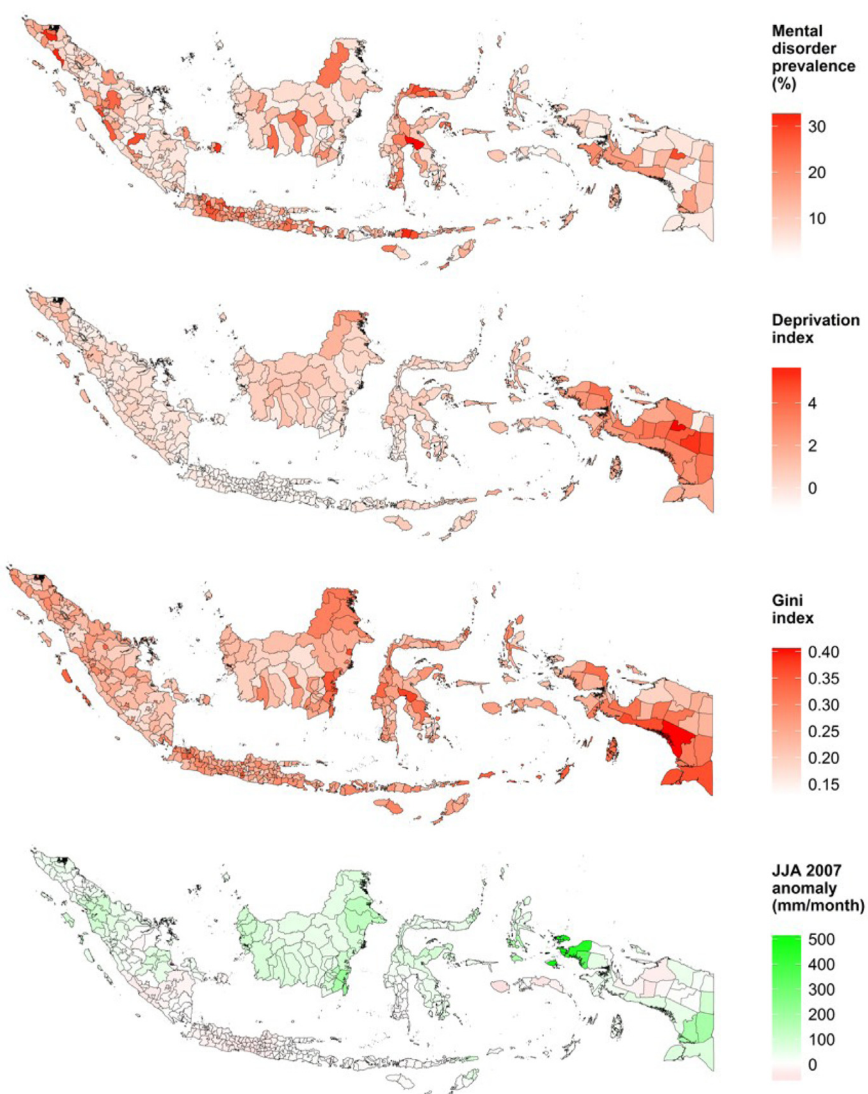

Fig. 2. Spatial distribution of common mental disorders, facility deprivation, income inequality and precipitation anomaly across 440 districts in Indonesia.

rest of Sumatra were generally wetter than normal. The highest precipitation anomaly for the season was recorded in West Papua.

5.2. Multivariate analysis without instrumenting for poverty variable

The results of multivariate analysis, assuming exogenous poverty, are presented in Table 2 under the headings 'Linear', 'Poisson', 'LPM' and 'Probit'. Log per capita household expenditure is found to be statistically significant and negatively related with symptoms of mental illness in all four models. Parameterising the SRQ-20 score as a continuous variable, the linear model estimates that, *ceteris paribus*, a doubled per capita household expenditure is associated with a $0.24 \times \ln(2) = 0.16$ point reduction in the SRQ-20 score (better mental health), though it must be noted that this modelling technique does not take the skewness and the non-negativity of the SRQ-20 into account. For that reason, we fit a Poisson model, which suggests that a 1% increase in consumption expenditure is associated with a 0.11% reduction in symptoms of mental illness. This estimate means that the change in an individual's mental health status is relatively inelastic to the change in his or her consumption. The negative association remains consistent even when mental health is treated as a dichotomous variable. Both linear probability and probit models suggest that, for a typical Indonesian, a doubled consumption expenditure is associated with an approximately $0.02 \times \ln(2) = 0.01$ lower probability of having clinically significant symptoms of common mental disorders. These results demonstrate that the negative relationship between poverty and mental health is robust to distributional assumption and to alternative parameterisation.

Although frequent smoking was found to be associated with better mental health in the bivariate analysis presented previously, this is no longer the case in the multivariate analysis. After adjusting for potential confounders, frequent smokers are now estimated to have a 0.02 higher probability of having clinically significant symptoms of common mental disorders compared to those who smoke occasionally and those who do not smoke at all. Of the two contextual variables, only income inequality is statistically significant. A 0.1 point increase in the district-level Gini index (rising inequality) is associated with a 0.03 higher probability of having mental illness. This correlation provides weak support for the hypothesis that income distribution exerts a significant effect on the mental health of the population over and above the effect of individual income (Wilkinson and Pickett, 2010). The estimates for other covariates generally remain similar to those reached through the simple bivariate analysis.

5.3. Multivariate analysis after instrumenting for poverty variable

The results of multivariate analysis, assuming endogenous poverty, are presented in Table 2 under the headings 'Linear-IV', 'Poisson-IV', 'LPM-IV' and 'Probit-IV'. Apart from the assumption, these models are identical to those discussed above. We specify precipitation anomaly in two climatological seasons (MAM and JJA 2007) as instruments for per capita household consumption expenditure. Both climatological seasons coincide with the onset of the dry season in Indonesia; the JJA season also covers the start of the Riskesdas fieldwork (August 2007). The statistically significant result of test of the endogeneity of the instrumented regressor allows us to reject the null hypothesis that the poverty variable can actually be treated as exogenous. In investigating the strength of the instruments, we reject the null hypothesis that the instrument set is weak: the Kleibergen-Paap rank Wald F-statistic ($F = 21.04$) is well above the 10% critical value of the Cragg–Donald statistic ($F = 19.80$), although we note that this critical value is appropriate only for the i.i.d. normal sample (Baum et al., 2007). That precipitation anomaly strongly predicts consumption expenditure over and above the effect of other exogenous covariates should not be particularly surprising. This can be explained by the fact that, in 2007, nearly half (41%) of the members of the Indonesian labour

Table 2
Riskesdas 2007 national sample aged 15 or older ($N = 577{,}548$).

Predictors	Mental health score				Probable caseness			
	Linear	Linear-IV	Poisson	Poisson-IV	LPM	LPM-IV	Probit	Probit-IV
Log(PCE)	−0.24(0.05)‡	−1.31(0.55)†	−0.11(0.03)‡	−0.62(0.26)†	−0.02(0.00)‡	−0.09(0.04)†	−0.02(0.00)‡	−0.09(0.05)*
Age 25–34	0.02(0.02)	0.03(0.02)	0.01(0.01)	0.01(0.01)	−0.00(0.00)	−0.00(0.00)	−0.00(0.00)†	−0.00(0.00)†
Age 35–44	0.09(0.03)‡	0.14(0.04)‡	0.05(0.01)†	0.07(0.02)‡	−0.00(0.00)	0.00(0.00)	−0.00(0.00)	0.00(0.00)
Age 45–54	0.21(0.04)‡	0.34(0.07)‡	0.10(0.02)‡	0.16(0.04)‡	0.00(0.00)	0.01(0.01)†	0.00(0.00)	0.01(0.01)*
Age 55–64	0.41(0.05)‡	0.51(0.07)‡	0.18(0.02)‡	0.23(0.03)‡	0.02(0.00)‡	0.03(0.01)‡	0.02(0.00)‡	0.03(0.01)‡
Age 65+	0.81(0.06)‡	0.83(0.07)‡	0.30(0.03)‡	0.31(0.03)‡	0.06(0.01)‡	0.06(0.01)‡	0.04(0.00)‡	0.04(0.01)‡
Female	0.62(0.03)‡	0.63(0.03)‡	0.30(0.01)‡	0.30(0.01)‡	0.05(0.00)‡	0.05(0.00)‡	0.05(0.00)‡	0.05(0.00)‡
Never married	−0.09(0.03)†	−0.01(0.05)	−0.06(0.01)‡	−0.03(0.02)	−0.00(0.00)	0.00(0.00)	−0.00(0.00)	0.00(0.00)
Divorced	0.35(0.04)‡	0.33(0.05)‡	0.13(0.02)‡	0.11(0.02)‡	0.03(0.00)‡	0.03(0.00)‡	0.03(0.00)‡	0.02(0.00)‡
Widowed	0.26(0.03)‡	0.25(0.04)‡	0.05(0.01)‡	0.05(0.01)‡	0.03(0.00)‡	0.03(0.00)‡	0.01(0.00)‡	0.01(0.00)‡
Middle school	−0.30(0.03)‡	−0.13(0.09)	−0.14(0.01)‡	−0.06(0.04)	−0.02(0.00)‡	−0.01(0.01)	−0.02(0.00)‡	−0.01(0.01)
High school	−0.44(0.03)‡	−0.09(0.17)	−0.22(0.02)‡	−0.05(0.08)	−0.03(0.00)‡	−0.01(0.01)	−0.04(0.00)‡	−0.01(0.02)
College	−0.55(0.04)‡	0.03(0.29)	−0.29(0.02)‡	−0.01(0.14)	−0.04(0.00)‡	−0.00(0.02)	−0.05(0.00)‡	−0.01(0.03)
Unemployed	0.25(0.03)‡	0.18(0.04)‡	0.11(0.01)‡	0.08(0.02)‡	0.02(0.00)‡	0.02(0.00)‡	0.02(0.00)‡	0.02(0.00)‡
Less physical activity	0.15(0.04)‡	0.23(0.05)‡	0.07(0.02)‡	0.10(0.02)‡	0.01(0.00)‡	0.02(0.00)‡	0.01(0.00)‡	0.02(0.00)‡
Frequent smoker	0.25(0.02)‡	0.24(0.02)‡	0.13(0.01)‡	0.12(0.01)‡	0.02(0.00)‡	0.02(0.00)‡	0.02(0.00)‡	0.02(0.00)‡
Heavy drinker	0.54(0.11)‡	0.52(0.11)‡	0.25(0.04)‡	0.24(0.05)‡	0.04(0.01)‡	0.04(0.01)‡	0.04(0.01)‡	0.04(0.01)‡
Chronic illness	1.26(0.04)‡	1.33(0.05)‡	0.44(0.01)‡	0.48(0.02)‡	0.11(0.00)‡	0.11(0.00)‡	0.08(0.00)‡	0.08(0.01)‡
Household size	−0.04(0.01)‡	−0.12(0.04)†	−0.02(0.00)‡	−0.06(0.02)†	−0.00(0.00)‡	−0.01(0.00)†	−0.00(0.00)‡	−0.01(0.00)†
District deprivation	−0.00(0.05)	−0.03(0.06)	−0.00(0.03)	−0.01(0.03)	−0.00(0.00)	−0.01(0.00)	−0.00(0.00)	−0.00(0.00)
District inequality	3.59(1.07)‡	4.18(1.17)‡	1.71(0.50)‡	1.83(0.54)‡	0.28(0.09)†	0.32(0.10)‡	0.28(0.09)‡	0.32(0.10)‡
Urban	−0.07(0.06)	0.24(0.19)	−0.04(0.03)	0.11(0.09)	−0.00(0.00)	0.02(0.01)	−0.00(0.00)	0.02(0.02)
Intercept	1.68(0.06)‡	1.50(0.11)‡	0.52(0.03)‡	0.41(0.07)‡	0.07(0.00)‡	0.06(0.01)‡		
Estimator	OLS	GMM	GMM	GMM	OLS	GMM	ML	ML
Instruments' validity		0.97		0.83		0.73		
Log(PCE)'s exogeneity		3.33*				3.33*		2.16
Instruments' strength		21.04				21.04		

Note: $^{*}p < 0.10$, $^{\dagger}p < 0.05$, $^{\ddagger}p < 0.01$.

force were employed in the agriculture sector while at the same time only 16% of the agricultural land was covered by irrigation infrastructure (World Bank, 2014). A test of overidentifying restrictions also returns favourable results. The non-significant Hansen's J-statistic seems to suggest that both instruments give the same information.

Having assessed the quality of the instruments, we now interpret the results. With continuous parameterisation, the linear model estimates that a doubled per capita household expenditure reduces the SRQ-20 score by approximately 1 point (better mental health), while the Poisson model estimates that a 1% increased consumption leads to a 0.62% decrease in symptoms of mental illness. In concordance, dichotomous parameterisation suggests that raising one's consumption twofold brings about a 0.06 point lower probability of having clinically significant symptoms of common mental disorders. These estimated effects are approximately five times stronger than those obtained prior to instrumenting for per capita household expenditure, hinting that perhaps the bias due to measurement error rather than simultaneity or reverse causality was more dominant. Notice that now, after instrumenting for poverty status, individuals' mental health status becomes moderately elastic to the change in consumption expenditure. A similar pattern was found earlier by Ettner (1996) who analysed data from the US. Overall, except for education variables, whose estimated effects have become statistically indistinguishable from zero, all other covariates remain in the same direction as they were prior to instrumenting for the poverty variable.

Table 3 displays the sensitivity of the estimated poverty effect to the set of control variables entered into the model. It appears that the effect is robust to the choice of model specification. In the online appendix accompanying this article, we further refit the model with (1) urban-rural stratification, (2) control function estimator and (3) random effects estimator. The finding remains: consumption-poor individuals have a higher probability of suffering from mental illness.

6. Discussion and conclusion

Despite the claim that poverty causes mental illness in low- and middle-income countries, empirical evidence remains scarce. Little has been done to address the question of whether the observed wealth–health relationship is causal or just associational. The present study attempts to fill this gap by exploiting seasonal precipitation anomaly as a form of natural experiment that randomly determines poverty status in Indonesia. Results suggest that poverty causes poor mental health. Holding all other covariates constant, halving one's consumption expenditure raises the probability of having mental illness by 0.06 point, or, in terms of elasticity, a 1% decrease in consumption brings about 0.62% more symptoms of common mental disorders. This study finds that the effect of poverty on mental health is approximately five times stronger than is conventionally estimated, which may be indicative of the fact that measurement error rather than reverse causality was the main source of bias (Ettner, 1996). The effect is robust to varying distributional assumption, model specification, estimation technique and sample stratification. This supports the general finding in social epidemiology (Lund et al., 2010).

The present study also investigates the association between district-level income inequality and mental health. It is consistently estimated that income inequality correlates negatively with mental health over and above the effect of poverty. Individuals living in unequal districts are found to have a higher probability of suffering from mental illness than those who live in more egalitarian districts. This is consistent with the recent finding of Filho et al. (2013), who conducted a multilevel study in the Brazilian context. This also weakly supports the broader idea of the income inequality hypothesis put forward by Wilkinson and Pickett (2010). Additionally, the present study found that women, older people and those who are divorced or widowed tend to have a higher probability of suffering common mental disorders. This is, again, consistent with the existing literature on mental health in developing countries. Finally, negative health behaviours such as less physical activity, frequent smoking and heavy drinking are all related to lower levels of mental health.

This study has a number of limitations. The first pertains to the core assumption of instrumental variable estimation. For this method to work properly, one must maintain three strong assumptions, namely the relevance condition, the validity condition and the exclusion restriction. Not all of these are testable. While it has been shown through the weak identification test that seasonal precipitation anomaly strongly predicts per capita household expenditure (hence satisfying the relevance condition), there is no empirical test capable of examining the exclusion restriction (Freedman, 2005, 2010; Hernán and Robins, 2006). This must be established *a priori*. The quality of an instrumental variable estimation is only as good as its story; here it rests ultimately on the untestable assumption that precipitation anomaly is indeed a random variate perfectly uncorrelated with any determinants of mental health, and that it does not affect an individual's mental health except through its influence upon consumption expenditure. The second limitation relates to the possible interpretation of the causal parameter recovered by instrumental variable estimation, namely as a local average treatment effect (LATE) (Angrist and Pischke, 2008). Under the LATE interpretation, the causal parameter obtained in this study is simply the average effect of poverty on mental health for individuals whose income fluctuates in accordance with the randomisation provided by the natural experiment (the average treatment effect of the compliers). Of course, generalising this causal effect to the entire population of Indonesia requires additional layers of assumption, but given that a large

Table 3
Estimates of Log(PCE) in different specifications.

Specifications	Mental health score		Probable caseness	
	Linear-IV	Poisson-IV	LPM-IV	Probit-IV
Full model	−1.31(0.55)†	−0.62(0.26)†	−0.09(0.04)†	−0.09(0.05)*
Without unemployed	−1.32(0.55)†	−0.63(0.26)†	−0.09(0.04)†	−0.09(0.05)*
Without less physical activity, frequent smoker, heavy drinker and chronic illness	−1.12(0.57)†	−0.51(0.26)†	−0.08(0.04)*	−0.08(0.05)
Without deprivation and inequality	−1.45(0.62)†	−0.70(0.30)†	−0.12(0.05)†	−0.11(0.06)*
Without unemployed, less physical activity, frequent smoker, heavy drinker and chronic illness	−1.12(0.57)*	−0.50(0.26)*	−0.08(0.04)*	−0.08(0.05)
Without unemployed, less physical activity, frequent smoker, heavy drinker, chronic illness, deprivation and inequality	−1.17(0.64)*	−0.53(0.29)*	−0.10(0.05)*	−0.09(0.06)

Note* $p < 0.10$, †$p < 0.05$, ‡$p < 0.01$.

proportion of the Indonesian workforce is employed in the largely rain-dependent agriculture sector, we believe that even the LATE parameter is worthy of consideration. This study is also limited by the cross-sectional nature of the data. Future studies may take advantage of a longitudinal design so that temporal order can be incorporated into the model.

Despite its limitations, the present study contributes to the literature on mental health in developing countries in several ways. First, this study is among the few studies that attempt to address the endogeneity problem in the estimation of the mental health effect of poverty. Second, using a large and representative data from Indonesia, this study demonstrates that the adverse effect of poverty on mental health is not merely attributed to the self-selection bias that threatens small-sample community or facility studies. Third, considering both the use of a standard mental health and poverty measure and the fact that Indonesia is the most populous developing country after China and India, this study provides a finding that is suitable for cross-national comparison. Finally, the present study shows that poverty remains an important determinant of mental health irrespective of whether it is treated as an exogenous or as an endogenous variable. Indonesian policy makers now have reason to believe that poverty alleviation efforts can have considerable impact on the mental health of the population. Mental health can be improved not only by influencing individuals' health knowledge and behaviour but also by implementing a more equitable economic policy. Policy makers may also want to consider a greater public investment in the long-neglected mental health service sector, which would certainly benefit the nation as a whole given that the burden of mental illness is borne not only by the patients but also by their family members. Additionally, research has shown that mental illness is costly for a nation's economy (Lund et al., 2013). Furthermore, according to the referral scheme of Indonesia's recently launched version of the universal health care system (The Lancet, 2014), every prospective patient is required to report to the nearest primary care centre prior to visiting a hospital; mental health care service, then, must be surely made available at the lowest level of the referral hierarchy. Unless such a provision is available, the mental health of Indonesians will continue to be overlooked.

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.socscimed.2014.05.005.

References

Adler, N.E., Ostrove, J.M., 1999. Socioeconomic status and health: what we know and what we don't. Ann. N. Y. Acad. Sci. 896 (1), 3–15.

Angrist, J.D., Pischke, J., 2008. Mostly Harmless Econometrics: An Empiricist's Companion. Princeton University Press, Princeton, New Jersey.

Baum, C.F., Schaffer, M., Stillman, S., 2007. Enhanced routines for instrumental variables/generalized method of moments estimation and testing. Stata J. 7 (4), 465–506.

Beusenberg, M., Orley, J., 1994. A User's Guide for the Self Reporting Questionnaire (SRQ). World Health Organization, Geneva. Available at: http://apps.who.int/iris/handle/10665/61113 (accessed 22.01.14.).

Björkman-Nyqvist, M., 2013. Income shocks and gender gaps in education: evidence from Uganda. J. Dev. Econ. 105, 237–253.

Bound, J., Jaeger, D.A., Baker, R.M., 1995. Problems with instrumental variables estimation when the correlation between the instruments and the endogeneous explanatory variable is weak. J. Am. Stat. Assoc. 90 (430), 443–450.

Cameron, A.C., Trivedi, P.K., 2005. Microeconometrics: Methods and Applications. Cambridge University Press, New York.

Cameron, A.C., Trivedi, P.K., 2010. Microeconometrics Using Stata, Revised ed. Stata Press, College Station, Texas.

Chen, S., Zhao, G., Li, L., Wang, Y., Chiu, H., Caine, E., 2009. Psychometric properties of the Chinese version of the self-reporting questionnaire 20 (SRQ-20) in community settings. Int. J. Soc. Psychiatry 55 (6), 538–547.

Chin, B., 2010. Income, health, and well-being in rural Malawi. Demogr. Res. 23 (35), 997–1030.

Cutler, D.M., Katz, L.F., 1992. Rising inequality? Changes in the distribution of income and consumption in the 1980's. Am. Econ. Rev. 82 (2), 546–551.

Deaton, A., Zaidi, S., 2002. Guidelines for Constructing Consumption Aggregates for Welfare Analysis. Living Standards Measurement Study Working Paper No. 135. The World Bank.

Dohrenwend, B.P., Levav, I., Shrout, P.E., Schwartz, S., Naveh, G., Link, B.G., Skodol, A.E., Stueve, A., 1992. Socioeconomic status and psychiatric disorders: the causation-selection issue. Science 255 (5047), 946–952.

Dzator, J., 2012. Hard times and common mental health disorders in developing countries: insights from urban Ghana. J. Behav. Health Serv. Res. 40 (1), 71–87.

Ecob, R., Smith, G.D., 1999. Income and health: what is the nature of the relationship? Soc. Sci. Med. 48 (5), 693–705.

Ettner, S., 1996. New evidence on the relationship between income and health. J. Health Econ. 15 (1), 67–85.

Filho, A.D., Kawachi, I., Wang, Y.P., Viana, M.C., Andrade, L.H., 2013. Does income inequality get under the skin? A multilevel analysis of depression, anxiety and mental disorders in São Paulo, Brazil. J. Epidemiol. Community Health 67 (11), 966–972.

Freedman, D., 2005. Statistical Models: Theory and Practice. Cambridge University Press, New York.

Freedman, D., 2010. Statistical Models and Causal Inference: A Dialogue with the Social Sciences. Cambridge University Press, New York.

Frijters, P., Haisksystemen-DeNew, J.P., Shield, M.A., 2005. The causal effect of income on health: evidence from German reunification. J. Health Econ. 24 (5), 997–1017.

Ganihartono, I., 1996. Psychiatric morbidity among patients attending the Bangetayu community health centre in Indonesia. Buletin Penelitian Kesehatan 24 (4), 42–51.

Ghubash, R., Daradkeh, T., El-Rufaie, O.F., Abou-Saleh, M.T., 2001. A comparison of the validity of two psychiatric screening questionnaires: the Arabic general health questionnaire (AGHQ) and self-reporting questionnaire (SRQ-20) in UAE, using receiver operating characteristic (ROC) analysis. Eur. Psychiatry 16 (2), 122–126.

Giang, K.B., Allebeck, P., Kullgren, G., Tuan, N.V., 2006. The Vietnamese version of the self-reporting questionnaire 20 (SRQ-20) in detecting mental disorders in rural Vietnam: a validation study. Int. J. Soc. Psychiatry 52 (2), 175–184.

Glewwe, P., King, E.M., 2001. The impact of early childhood nutritional status on cognitive development: does the timing of malnutrition matter? World Bank Econ. Rev. 15 (1), 81–113.

Goldberg, E.M., Morrison, S.L., 1963. Schizoprenia and social class. Br. J. Psychiatry 109 (463), 785–802.

Gould, W., 22 August 2011. Use poisson rather than regress; tell a friend. The Stata Blog. Available at: http://blog.stata.com/2011/08/22/use-poisson-rather-than-regress-tell-a-friend/ (accessed 29.10.13.).

Hamad, R., Fernald, L.C.H., Karlan, D.S., Zinman, J., 2008. Social and economic correlates of depressive symptoms and perceived stress in South African adults. J. Epidemiol. Community Health 62 (6), 538–544.

Harding, T.W., De Arango, V., Baltazar, J., Climent, C.E., Ibrahim, H.H.A., Ladrido-Ignacio, L., Wig, N.N., 1980. Mental disorders in primary health care: a study of their frequency and diagnosis in four developing countries. Psychol. Med. 10 (2), 231–241.

Hernán, M.A., Robins, J.M., 2006. Instruments for causal inference: an epidemiologist's dream? Epidemiology 17 (4), 360–372.

Howe, L.D., Galobardes, B., Matijasevich, A., Gordon, D., Johnston, D., Onwujekwe, O., Patel, R., Webb, E.A., Lawlor, D.A., Hargreaves, J., 2012. Measuring socio-economic position for epidemiological studies in low- and middle-income countries: a methods of measurement in epidemiology paper. Int. J. Epidemiol. 41 (3), 871–886.

IHME, 2013. Global Burden of Disease (GBD) Visualizations. Institute for Health Metrics and Evaluation. Available at: http://www.healthmetricsandevaluation.org/gbd/visualizations/country (accessed 14.11.13.).

Imbens, G.W., Wooldridge, J.M., 2007. Control Function and Related Methods. *What's New in Econometrics?* NBER Mini-Course in Cambridge, Massachusetts. July 31-August 1, 2007. Available at: http://www.nber.org/WNE/WNEnotes.pdf (accessed 22.01.14.).

Irmansyah, I., Dharmono, S., Maramis, A., Minas, H., 2010. Determinants of psychological morbidity in survivors of the earthquake and tsunami in Aceh and Nias. Int. J. Ment. Health Syst. 4 (8), 1–10.

Kemenkes, 2008. Laporan Nasional Riskesdas 2007. Ministry of Health - The Republic of Indonesia, Jakarta. Available at: http://www.litbang.depkes.go.id/bl_riskesdas2007 (accessed 22.01.14.).

Kishore, K., Subbiah, A.R., Sribimawati, T., Diharto, S., Alimoeso, S., Rogers, P., Setiana, A., 2000. Indonesia Country Study. Asian Disaster Preparedness Center. Available at: http://archive.unu.edu/env/govern/ElNIno/CountryReports/pdf/indonesia.pdf (accessed 22.01.14.).

Levine, D., Yang, D., 2006. A Note on the Impact of Local Rainfall on Rice Output in Indonesian Districts. Research note. Available at: http://www-personal.umich.edu/~deanyang/papers/levineyang_ricerain.pdf (accessed 22.01.14.).

Lund, C., Breen, A., Flisher, A.J., Kakuma, R., Corrigall, J., Joska, J.A., Swartz, L., Patel, V., 2010. Poverty and common mental disorders in low and middle income countries: a systematic review. Soc. Sci. Med. 71 (3), 517–528.

Lund, C., Myer, L., Stein, D.J., Williams, D.R., Flisher, A.J., 2013. Mental illness and lost income among adult South Africans. Soc. Psychiatry Psychiatr. Epidemiol. 48 (5), 845–851.

Meer, J., Miller, D.L., Rosen, H.S., 2003. Exploring the health-wealth nexus. J. Health Econ. 22 (5), 713–730.
Meyer-Christoffer, A., Becker, A., Finger, P., Rudolf, B., Schneider, U., Ziese, M., 2011. GPCC Climatology Version 2011 at 0.5°: Monthly Land-Surface Precipitation Climatology for Every Month and the Total Year from Rain-gauges Built on GTS-Based and Historic Data. Available at: http://dx.doi.org/10.5676/DWD_GPCC/CLIM_M_V2011_025 (accessed 22.01.14.).
Miguel, E., Satyanath, S., Sergenti, E., 2004. Economic shocks and civil conflict: an instrumental variables approach. J. Polit. Econ. 112 (4), 725–753.
Milanovic, B., 1997. A simple way to calculate the Gini coefficient, and some implications. Econ. Lett. 56 (1), 45–49.
Muntaner, C., Eaton, W.W., Miech, R., O'Campo, P., 2004. Socioeconomic position and major mental disorders. Epidemiol. Rev. 26 (1), 53–62.
Myer, L., Stein, D.J., Grimsrud, A., Seedat, S., Williams, D.R., 2008. Social determinants of psychological distress in a nationally-representative sample of South African adults. Soc. Sci. Med. 66 (8), 1828–1840.
Nazara, S., 2010. The Informal Economy in Indonesia: Size, Composition and Evolution. The International Labour Organization, Jakarta. Available at: http://www.ilo.org/jakarta/whatwedo/publications/WCMS_145781/lang--en/index.htm (accessed 22.01.14).
Nichols, A., 2010. Regression for nonnegative skewed dependent variables. In: BOS10 Stata Conference 2, Stata User Group. Available at: http://repec.org/bost10/nichols_boston2010.pdf (accessed 07.11.13.).
Patel, V., 2007. Mental health in low- and middle-income countries. Br. Med. Bull. 81-82 (1), 81–96.
Paxson, C.H., 1992. Using weather variability to estimate the response of savings to transitory income in Thailand. Am. Econ. Rev. 82 (1), 15–33.
Pollock, J.I., Manaseki-Holland, S., Patel, V., 2006. Detection of depression in women of child-bearing age in non-western cultures: a comparison of the Edinburgh postnatal depression scale and the self-reporting questionnaire-20 in Mongolia. J. Affect. Disord. 92 (2–3), 267–271.
Poterba, J.M., 1989. Lifetime incidence and the distributional burden of excise taxes. Am. Econ. Rev. 79 (2), 325–330.
Santos Silva, J.M.C., Tenreyro, S., 2006. The log of gravity. Rev. Econ. Stat. 88 (4), 641–658.
Saraceno, B., Levav, I., Kohn, R., 2005. The public mental health significance of research on socio-economic factors in schizophrenia and major depression. World Psychiatry 4 (3), 181–185.
Savage, D., Fichera, E., 2013. Income, Rainfall Shocks and Health: An Instrumental Variable Approach. SSRN Scholarly Paper. Available at: http://papers.ssrn.com/abstract=2280049 (accessed 22.01.14.).
Scazufca, M., Menezes, P.R., Vallada, H., Araya, R., 2009. Validity of the self reporting questionnaire-20 in epidemiological studies with older adults: results from the Sao Paulo Ageing & Health Study. Soc. Psychiatry Psychiatr. Epidemiol. 44 (3), 247–254.
Schneider, U., Becker, A., Finger, P., Meyer-Christoffer, A., Rudolf, B., Ziese, M., 2011. GPCC Full Data Reanalysis Version 6.0 at 0.5°: Monthly Land-surface Precipitation from Rain-gauges Built on GTS-based and Historic Data. Available at: http://dx.doi.org/10.5676/DWD_GPCC/FD_M_V6_050 (accessed 22.01.14.).
Schneider, U., Becker, A., Finger, P., Meyer-Christoffer, A., Ziese, M., Rudolf, B., 2014. GPCC's new land surface precipitation climatology based on quality-controlled in situ data and its role in quantifying the global water cycle. Theor. Appl. Clim. 115 (1–2), 15–40.
Scholte, W.F., Verduin, F., van Lamm, A., Rutayisire, T., Kamperman, A., 2011. Psychometric properties and longitudinal validation of the self-reporting questionnaire (SRQ-20) in a Rwandan community setting: a validation study. BMC Med. Res. Methodol. 11 (116), 1–10.
Smith, J.P., 1999. Healthy bodies and thick wallets: the dual relation between health and economic status. J. Econ. Perspect. 13 (2), 145–166.
Stowasser, T., Heis, F., McFadden, D., Winter, J., 2011. "Healthy, Wealthy and Wise?" Revisited: An Analysis of the Causal Pathways from Socioeconomic Status to Health. NBER Chapters. Available at: http://ideas.repec.org/h/nbr/nberch/12443.html (accessed 22.01.14.).
Stratton, K.J., Aggen, S.K., Richardson, L.K., Acierno, R., Kilpatrick, D.G., Gaboury, M.T., Tran, T.L., Trung, L.T., Tam, N.T., Tuan, T., Buoi, L.T., Ha, T.T., Thach, T.D., Amstadter, A., 2013. Evaluating the psychometric properties of the self-reporting questionnaire (SRQ-20) in a sample of Vietnamese adults. Compr. Psychiatry 54 (4), 398–405.
Tampubolon, G., Hanandita, W., 2014. Poverty and mental health in Indonesia. Soc. Sci. Med. 106, 20–27.
The Lancet, 2014. Indonesia strides towards universal health care. The Lancet 383 (9911), 2.
Tol, W.A., Reis, R., Susanty, D., Jong, J., 2010. Communal violence and child psychosocial well-being: qualitative findings from Poso, Indonesia. Transcult. Psychiatry 47 (1), 112–135.
Wilkinson, R.G., Pickett, K., 2010. The Spirit Level: Why Equality Is Better for Everyone. Penguin Books, London.
Windmeijer, F., Santos Silva, J.M.C., 1997. Endogeneity in count data models: an application to demand for health care. J. Appl. Econ. 12 (3), 281–294.
World Bank, 2014. World Development Indicators (WDI), The World Bank Online Database. Available at: http://data.worldbank.org/indicator (accessed 22.01.14.).
Yang, D., Choi, H., 2007. Are remittances insurance? Evidence from rainfall shocks in the Philippines. World Bank Econ. Rev. 21 (2), 219–248.
Zimmerman, F., Katon, W., 2005. Socioeconomic status, depression disparities, and financial strain: what lies behind the income-depression relationship? Health Econ. 14 (12), 1197–1215.