Income, Psychological Well-being, and the Dynamics of Poverty*

M. Alloush†

July 14, 2018

Abstract

Evidence across disciplines suggests that economic well-being affects an individual's psychological well-being, while other studies show that psychological disorders can have substantial negative effects on individual income. Together these studies suggest a feedback loop that may trap some in poverty. However, estimating the causal links between income and psychological well-being is difficult due to this simultaneous causality. In this paper, I overcome this endogeneity with a panel GMM approach to estimate a dynamic system of equations that identifies both causal links. Using a nationally representative panel dataset from South Africa, I find evidence of impacts in both directions. Further investigation of the heterogeneity of these impacts shows that the average effect of changes in psychological well-being on income is mainly driven by the large effect of changes near the threshold used by psychologists to screen for depression. Furthermore, the effect of changes in income on psychological well-being is especially pronounced among the poor, indicating the possibility of a strong feedback loop among an especially vulnerable subgroup – the poor with low levels of psychological well-being. An impulse response function analysis suggests that this bi-directionality nearly doubles the long-term impact of shocks while a simulation using the estimated equations suggests that this relationship can explain prolonged poverty spells and low resilience to shocks. A formal test for poverty traps shows that individuals with low levels of psychological well-being exhibit different income dynamics that suggest the existence of a multi-equilibrium poverty trap.

Job Market Paper: Latest version available **here.**

*I am grateful for the support and guidance of my advisors Michael Carter, Travis Lybbert, Dalia Ghanem, and Ashish Shenoy throughout this project. This paper has benefited from discussions with Bulat Gafarov, Malcolm Keswell, Michael Gechter, Takuya Ura, and Diana Moreira among other conference and seminar participants. I thank Murray Leibbrandt and the team at the South Africa Labor and Development Research Unit for their helpful comments and for their commitment to keeping the psychological well-being module in the National Income Dynamics Study of South Africa.

†University of California, Davis, Department of Agricultural and Resource Economics. One Shields Ave, Davis, CA 95616. Email: mmism@ucdavis.edu

1 Introduction

Psychological disorders are estimated to account for nearly 13% of the overall global disease burden (Collins et al., 2011). At any given point in time, it is estimated that nearly 4.4% of people worldwide suffer from depression – the most common psychological disorder – with higher rates in in developing countries (5.5%) and, in 2015, depressive disorders[1] accounted for nearly 7.5% of all Years Lived with Disability (YLD) globally (World Heath Organization, 2017). Despite the ubiquity of psychological disorders, empirical evidence on their micro-economic consequences is limited, especially in developing countries. This is at least partially due to the difficulty of empirically untangling the causal relationships between psychological well-being and income. While a change in an individual's psychological well-being *can* influence their earnings, economic well-being likely play a significant role in determining an individual's state of mental health. This endogeneity makes it difficult to pin down estimates of causal links using observational data. In this paper, I aim to fill this gap by estimating both causal links simultaneously using a panel Generalized Method of Moments (GMM) approach and a nationally representative dataset from South Africa and investigating the implications on the dynamics of poverty.

The bi-directional relationship between psychological well-being and economic well-being and its potential to put some individuals in a vicious cycle of poverty is well established in the psychology literature. The social drift hypothesis posits that individuals with mental illness are more likely to enter into or remain in poverty due to reduced productivity, loss of earnings, and wasteful spending. In addition, the social causation hypothesis states that conditions of poverty increase the risk of mental illness, and affect psychological well-being through malnutrition, violence, and social exclusion (Lund et al., 2011). However, most

[1] Depressive disorders are characterized by sadness, feelings of tiredness, loss of interest or pleasure, disturbed sleep or appetite, feelings of guilt or low self-worth, and poor concentration. They can be long lasting or recurrent, substantially impairing an individual's ability to function at work or school or cope with daily life. Depressive disorders include two main sub-categories: major depressive disorder/episode, which involves symptoms such as depressed mood, loss of interest and enjoyment, and decreased energy typically lasting about 6 months; and dysthymia, a persistent or chronic form of mild depression that has similar symptoms to depressive episode, but tend to be less severe and longer lasting.

evidence on the causal links between economic and psychological well-being is limited in its scope and involves very narrow subsets of the population. Given the prevalence of psychological disorders around the world, the question as to whether the relationship between income and psychological well-being poses an impediment for some to achieve their full economic potential should be of interest to economists and policymakers alike. Understanding this relationship may pave the way for more effective poverty-alleviation policy.

This paper overcomes the difficulty of identification due to simultaneous causality by extending panel data methods and using a GMM approach to estimate a system of dynamic and simultaneous equations in order to answer two main questions. First, does psychological well-being affect an individual's own income? Second, does economic well-being play a significant role in determining an individual's psychological well-being? The estimates show that a reduction in psychological well-being decreases individual income in a nonlinear way and at the same time, a decrease in household income is estimated to increase depressive symptoms, especially among the poor.

A main contribution of this paper is estimating the impact of psychological well-being and depression on income, which is not yet well-understood in the economics literature. Only a few studies measure the causal effects of mental health on employment and income in an empirically robust manner among general populations. The existing evidence suggests that decreased mental health significantly reduces the likelihood of employment (Chatterji, Alegria, & Takeuchi, 2011; Frijters, Johnston, & Shields, 2014; Peng, Meyerhoefer, & Zuvekas, 2015). Furthermore, experimental work in the psychology and medical literature show that among those already suffering from depression, interventions such as therapy and antidepressants aimed at reducing depressive symptoms positively influence several economic outcomes such as increased labor force participation at the extensive and intensive margins (Bolton et al., 2003; Ran et al., 2003). This paper adds to this literature by estimating the effects of changes in psychological well-being on income in a nationally representative sample in a developing country while also demonstrating the nonlinearity of these effects.

This analysis also adds to a growing literature on the impact of income on psychological well-being.[2] Economists have increasingly measured this effect and the evidence generally indicates that increased income improves overall levels of psychological well-being (Frijters, Haisken-DeNew, & Shields, 2004, 2005; Gardner & Oswald, 2007; Haushofer & Shapiro, 2016; McInerney, Mellor, & Nicholas, 2013). Moreover, this paper contributes to a growing field aimed at understanding the multitude of stresses faced in poverty. The psychological consequences of poverty are gaining increased attention among behavioral economists who are investigating the mechanisms through which the stresses faced in poverty can affect economic decision-making (Mani, Mullainathan, Shafir, & Zhao, 2013; Schilbach, 2015; Schilbach, Schofield, & Mullainathan, 2016). It is likely that one avenue through which this may occur is lower levels of mental health (Haushofer & Fehr, 2014). Specifically relevant to this paper is the theoretical work by De Quidt and Haushofer (2016) which introduces depression in a way familiar to economists and models the potential negative effects of depression on labor supply. This paper adds to this field by empirically estimating both causal links – that of psychological well-being on income and the effect of income on psychological well-being – and exploring the implications of this bi-directional relationship on poverty dynamics.

In order to empirically untangle the relationship between income and psychological well-being, I extend the panel data methods developed by Arellano and Bond (1991) to estimate a system of simultaneous and dynamic equations.[3] The results show evidence of impacts on average in both directions. A closer analysis shows that changes in the lower

[2]It is important to differentiate between psychological well-being and subjective well-being which is the subject of many different studies over the years (see for example Clark, D'Ambrosio, and Ghislandi (2013); Graham and Pettinato (2002); Kahneman and Deaton (2010); Stevenson and Wolfers (2013); Winkelmann and Winkelmann (1998)). In this paper, the CES-D scale measures psychological well-being and I contrast my results with results from another working paper using questions on life satisfaction and happiness which measure subjective well-being (Alloush, 2018). The estimates of the impact of changes in income on these measures are different in meaningful ways which suggests that the measures – despite being correlated – capture different states of well-being.

[3]While the panel GMM approach does not depend on exogenous shocks to income or psychological well-being, it requires assumptions on the error terms for consistent estimation. The main specification used assumes no serial correlation in the errors. This rules out correlation in shocks to income and psychological well-being over time after state dependence, individual fixed effects, and other time varying observable characteristics are taken into account. The results are robust to the use of a less restrictive specification that allows for serial correlation across one time period.

end of the Center for Epidemiologic Studies Depression (CES-D) scale do not seem to affect income,[4] however, near the threshold used by psychologists to screen for depression, I find large effects on individual income. The estimates predict that a 1 standard deviation (SD) increase in the CES-D score (increase in depressive symptoms) for the average individual decreases their income by nearly 23%. Moreover, the results suggest that one possible avenue through which the impact on income occurs is a decreased likelihood of being economically active. At the same time, I find that a 20% increase in household income per capita reduces an individual's CES-D score by 0.41 points (0.1 SD) on average.[5] I also find similar statistically significant estimates when using other measures of economic well-being, namely, food expenditure per capita and a household wealth index. Further investigation of the heterogeneity of the impact by baseline income levels shows that the impact is larger among the poor.

These results indicate that income and psychological well-being are intertwined and that a particularly vulnerable group, namely the poor with low levels of psychological well-being, may be disproportionately affected by shocks. Simulations of the estimated system of dynamic equations shows that this feedback loop plays a role in prolonging poverty spells and decreasing resilience to negative shocks. This should inform policymakers about the potentially large impacts of negative income shocks on an especially vulnerable group. Formal tests do not detect a poverty trap among the whole sample, but when restricting the sample to individuals who exhibit low levels of psychological well-being, the income dynamics implied are markedly different and suggest the existence of a multi-equilibrium poverty trap.

While the results do mainly stress the potential negative consequences of the relationship between poverty and psychological well-being, there is a positive story to tell. Welfare programs may have an added benefit of positive impacts on psychological well-being, which

[4] Low CES-D scores indicate fewer depressive symptoms and can be viewed as high levels of psychological well-being.

[5] Back-of-the-envelope calculations suggest that the estimated magnitude of the effect of changes in household income is similar to the effect of cash transfers experimentally estimated by Haushofer and Shapiro (2016).

is in itself an important goal, but it may also enhance an individual's capability to further increase their economic well-being. In this sense, psychological well-being is both a constitutive freedom and an instrumental one (Sen, 1999). The results in this paper suggest that psychological well-being is an important dimension of poverty that may explain some of the persistence of poverty. At the same time, this analysis reaffirms the conclusion of Haushofer and Fehr (2014) that stresses the importance of considering psychological variables as dimensions for novelty in poverty-alleviation programs.

The rest of this paper is structured as follows. Section 2 discusses psychological well-being and depression, their economics relevance, and measurement. In Section 3, I introduce the dataset and highlight relevant descriptive statistics. Section 4 outlines the main empirical strategy and the key assumptions required for consistency, and Section 5 presents the results. Finally, Section 6 discusses some implications of the results on poverty dynamics using impulse response function analysis, simulations, and a test for poverty traps. Section 7 concludes.

2 Psychological Well-being and Depression

In this paper, I use the Center for Epidemiologic Studies Depression (CES-D) scale as a measure of psychological well-being. While this scale can be used as a continuum that proxies for psychological well-being Siddaway, Wood, and Taylor (2017), a high score on the continuum identifies individuals who are likely suffering from depression, the most common psychological disorder. In this section, I present some of the evidence on the connection between depression and economic well-being in both the psychology and economics literature and I further discuss the CES-D scale.

2.1 Significance

It is estimated that nearly 4.4% of the world's population suffers from depression at any point in time and improved measurement in recent years has suggested that it is the leading cause of disability worldwide and contributes to nearly 14% of the global disease burden (Collins et al., 2011; Friedrich, 2017). A major depressive episode (MDE) is often debilitating to an individual, and its impact can be substantial. It is associated with diminished quality of life, significant functional impairment, and higher risk of mortality (Hays, Wells, Sherbourne, Rogers, & Spritzer, 1995; Spijker et al., 2004). Reduced functioning in occupational and social roles is pervasive among those suffering from depression, and studies find that these disabilities decrease if depressive symptoms are alleviated but are chronic if depressive symptoms persist (Ormel, Oldehinkel, Brilman, & Brink, 1993).[6] While some of these effects may be experienced with gradual increases in depressive symptoms, the impacts are especially pronounced with the onset of an MDE and continue to worsen with the severity of depression (Siddaway et al., 2017; Spijker et al., 2004).[7]

Prominent psychiatrist Aaron Beck's (1967) exposition on depression provides a detailed analysis of the symptoms and behavioral changes associated with depression. De Quidt and Haushofer (2016) summarize Beck's seminal work on depression and highlight ways in which several different symptoms and consequences of depression could be of interest to economists. An MDE can affect individuals in various ways including effectively altering elements of an individual's economic decision-making process. In brief, depression is associated with negative expectations and low self-evaluation, indecisiveness and paralysis of the will, withdrawal and rumination, as well as fatigue and reduced gratification. There is an extensive literature in psychology illustrating the effect of depression on preferences, perception, and cognitive and executive functioning.[8] De Quidt and Haushofer (2016) show,

[6] While the impacts of some psychological disorders have been shown to differ across cultures, the findings on depression show consistency across many different contexts (Ormel et al., 1994).

[7] The functional impairments associated with an MDE are likely to affect an individual's earnings, however, these causal effects have not been well estimated in the general population.

[8] For example lower levels of mental well-being show reduced responsiveness to reward and an increased

using a theoretical model, how an altered self-evaluation could adversely affect labor supply. It is possible and likely that depression – through its many symptoms – can have a substantial impact on one's economic decision-making and consequent outcomes. This paper shows, in reduced form, how changes in depressive symptoms affect an individual's income.

2.2 Economics and Depression

Experimental evidence in psychology and medicine have shown that among a sample of individuals diagnosed with depression, decreasing depressive symptoms through therapy and/or antidepressants significantly improves several economic outcomes including employment at the intensive and extensive margins (Bolton et al., 2003; Ran et al., 2003). These studies involve samples that are not random: specifically, it involves patients who are suffering from depression and sought treatment. In economics, studies that look at the impact of psychological well-being on economic outcomes are rare; however, recent work uses exogenous negative shocks to psychological well-being (using death of friends as an instrumental variable) to show significant negative impacts on employment (Frijters et al., 2014). Using panel data from Australia, the authors find that, among adults, a one standard deviation decrease in mental health decreased the likelihood of employment by 30%.

Recent interest in economics has mainly focused on the reverse causal link, the effect of income and poverty on mental health. Several studies use exogenous shocks to income to show that income does affect mental health (Frijters et al., 2004, 2005; Gardner & Oswald, 2007). For example, Gardner and Oswald (2007) compare British lottery players to a control group of other lottery players and find that those who win the lottery show higher levels of psychological well-being. In recent work, changes in wealth due to the great recession are

negative evaluation of self (Harvey et al., 2004; Snyder, 2013). Moreover, depressive symptoms are associated with altered decision-making: individuals choose fewer advantageous options in economic games, are more risk averse (Smoski et al., 2008), and are less flexible in their choices (Cella, Dymond, & Cooper, 2010). Other studies find that depression is generally associated with impaired decision-making ability and more suboptimal decisions than those in the control groups (Murphy et al., 2001; Yechiam, Busemeyer, & Stout, 2004). Depressive symptoms are shown to be associated with lower cognitive functioning (Hubbard et al., 2016).

shown to affect the likelihood of depression (McInerney et al., 2013).[9]

Recent experimental studies on the impact of cash transfers have increasingly focused on the potential psychological benefits of these transfers. In a recent paper, Haushofer and Shapiro (2016) find that large once-off cash transfers to poor households in Kenya reduced stress by 0.26 SD and decreased depressive symptoms – measured by a 1.2-point reduction in the CES-D 20 scale.[10] Furthermore, Banerjee et al. (2015), in a multi-country study, find that a multi-faceted poverty graduation program improved mental health by 0.1 SD.[11] The authors find that these effects are sustained two years after the program. Other experimental and quasi-experimental studies suggest that cash transfer programs reduce the incidence of depression among beneficiaries (Macours, Schady, & Vakis, 2012; Ozer, Fernald, Weber, Flynn, & VanderWeele, 2011).

There is a clear pattern in these studies: income does affect psychological well-being. However, it would be a stretch to generalize these results to speak about the impacts of naturally occurring changes in income, some of which may be earned, on psychological well-being. Many of the causal estimates are driven by either shocks or unearned cash inflow (such as lotteries). Moreover, cash transfers mainly target the poor and thus impacts of these programs cannot necessarily be generalized to be the impact of income on mental health in the general population. This paper adds to the literature by estimating both relationships using nationally representative data from a developing country.

2.3 CES-D

The measure of psychological well-being used in this paper is the 10-item Center for Epidemiologic Studies Depression (CES-D) scale. The CES-D scale was developed for use in

[9] Related research on the consequences of unemployment shows that unemployment due to plant closures decreased levels of mental health of both the unemployed and his/her spouse (Fasani, Farre, & Mueller, 2015; Marcus, 2013).

[10] The CES-D scale in Haushofer and Shapiro (2016) is the CES-D 20 scale which is the original longer version of the CES-D 10 that is used in this paper. I discuss the comparability of two scales in Section 2.3.

[11] The index of mental health used by these authors includes CES-D scores. It is important to note that these programs involve more than just a transfer of income or assets and thus the effects on psychological well-being cannot be attributed only to increases in income.

studies to assess depressive symptoms and screen for depression in the general population (Radloff, 1977). It is widely-used to measure depressive symptoms (Santor, Gregus, & Welch, 2006), and in its original format it contains 20 questions that ask individuals how often in the last week they felt certain emotions related to depression and are scored accordingly. For negative feelings such as how often an individual felt loneliness or an inability to get going, the respondent gets a 0 score if they respond with "Not at all or rarely," 1 for "Some or little of the time," 2 for "Occasionally," and 3 for "All the time." For positive statements such as "feeling hopeful," the scores are reversed. The answer numbers are then added for all the questions to get an overall CES-D score with a range of 0 to 60.[12] A higher overall CES-D score indicates that one is experiencing more pronounced depressive symptoms. Analysis of the shortened 10-item CES-D scale attained satisfactory prediction accuracy and reliability in assessing significant depressive symptoms and correlate very highly with the full 20-item questionnaire (Zhang et al., 2012). Furthermore, the CES-D scale is shown to be reliable and stable over short periods of time (González et al., 2017; Saylor, Edwards, & McIntosh, 1987).

While CES-D was developed to screen for depression, it is often viewed as a continuum of psychological well-being (Siddaway et al., 2017; Wood, Taylor, & Joseph, 2010). However, scores beyond certain thresholds indicate that an individual may be suffering from depression. In the 10-item CES-D used in this paper, a score of 10 or more is the threshold that is usually used. This suggests that when considering the impact of decreased psychological well-being, the effects may be nonlinear and especially pronounced around this threshold.

It is important to consider whether the CES-D is valid in South Africa as a measure of psychological well-being. Language and culture likely affect the way questions are understood and answered (Samuels & Stavropoulou, 2016). However, the CES-D 10 is widely used in South Africa and has been verified for use as an effective initial screening tool by several different studies (Hamad, Fernald, Karlan, & Zinman, 2008; Johnes & Johnes, 2004; Myer

[12] The range is 0 to 30 for the CES-D 10 used in the paper.

et al., 2008). In addition, Hamad et al. (2008) found that the CES-D scale is internally consistent in South Africa. A recent study by Baron, Davies, and Lund (2017) suggests that 11 may be a more appropriate threshold to screen for depression using the CES-D 10 among most populations in South Africa.

Another characteristic of CES-D that makes it useful is that its questions do not explicitly mention psychiatric illnesses. This helps mitigate the effect of stigma on the quality of data. Mental illnesses are highly stigmatized in South African communities (Hugo, Boshoff, Traut, Zungu-Dirwayi, & Stein, 2003), and this is evident in the data where the rate of response when asked about specific mental illnesses are extremely low. On the other hand, response rate on the CES-D section is high where on average 89% of individuals across all four waves answer all 10 questions.

I use the CES-D scale as the main measure of psychological well-being throughout this paper, which facilitates comparison with other literature on mental health and depression. The next section presents the source of the data and presents some descriptive statistics and highlights key correlations with CES-D.

3 Data and Descriptive Statistics

3.1 Data

The data used in this analysis come from the South Africa National Income Dynamics Study (NIDS), a panel survey conducted by the South Africa Labor and Development Research Unit at the University of Cape Town. The first survey wave of this study was conducted in 2008 with households interviewed every two years since then. The survey study began with a nationally representative sample of over 28,000 individuals (17,000 adults) in 7,300 households. Data is collected on many socio-economic variables that include expenditure, labor market participation and economic activity, fertility and mortality, migrations, income, education, and anthropometric measures. The data are publicly available and can be downloaded from the NIDS website.[13]

I use data from all four available waves of the NIDS. I restrict the sample to adults who completed the adult questionnaire in all four waves (years 2008, 2010, 2012, and 2014) which effectively includes only those who were at least 16 years old in the first wave. The resulting sample size is 6,975 individuals. Table 1 presents some descriptive statistics of the this sample: it is slightly poorer on average and a larger share is female than the nationally representative fourth wave sample of NIDS.[14]

The NIDS dataset contains detailed information on household income and expenditure in addition to individual income. While I mainly choose to use household income per capita throughout the analysis, I also use food expenditure per capita and a wealth index as measures of economic well-being to test the robustness of the results. On the other hand, when estimating the effect of mental well-being on income, I use an individual's own income as the dependent variable as an individual's mental well-being may influence her own income more directly than household-level measures of income.[15]

Most importantly to this analysis, NIDS contains the 10-item Center for the Epidemiological Studies Depression (CES-D) Scale. This is unprecedented in a nationally representative panel survey in a developing country.

3.2 Descriptive Statistics

South Africa is a middle-income country with one of the highest levels of income inequality in the world. Recent reports estimate that nearly 54% of the population is living in poverty and about 20% live in extreme poverty (Leibbrandt, Finn, & Woolard, 2012). The mean household income per capita (standard deviation in brackets) has increased from 1,672 ZAR

[13]Website can be found at http://www.nids.uct.ac.za/

[14]Comparing means and variances for key variables across those who completed the individual questionnaire in all four waves and those who did not (and consequently were not in the sample used in this analysis) showed to discernible differences.

[15]For both measures of income, extreme changes in both household and individual income suggest mismeasurement or very unusual cases. I trim the sample of the top and bottom 0.5% of changes in household income and individual income. Results are robust to trimming the top 1,2.5, and 5% instead.

(3,314) to 2,242 ZAR (2,934) in 2014.[16] In the sample used in this analysis, the mean CES-D score (standard deviation in brackets) for the four waves starting in 2008 is 8.17 (4.39), 7.13 (4.18), 7.16 (4.35), 6.95 (4.20). There seems to be a downward trend in the average CES-D score. The incidence of scores above 10 show a similar pattern and decrease from about 35% in 2008 to 25% in 2014. Figure 1 shows histograms of the CES-D scores in 2014 (top left) and 2012 (top right) and the changes in CES-D between 2012 and 2014 (bottom left). While the changes for the whole sample are centered around 0, the changes for those with scores in wave three that are eight and above are centered below zero. However, it is clear that a significant portion of this sub-sample experiences increases in their CES-D scores despite already having high scores.

Figure 2 graphs average CES-D score among income per capita and expenditure per capita deciles for all four waves. It is clear from the figure that the average CES-D scale decreases among those in higher income and expenditure deciles. These figures illustrate correlation, but are not causal. The next section outlines the empirical strategy to estimate the causal relationships between income and CES-D.

4 System of Equations and Estimation Strategy

The main source of endogeneity when studying the relationship between mental health and income is reverse causality. Psychological well-being has an impact on an individual's own earnings, but at the same time, income or the level of economic well-being affects their psychological well-being. Conceptually, the relationship between income and psychological well-being can be described using a system of simultaneous equations. To simplify, I assume that household income per capita is a proxy for economic well-being and plays a role in determining psychological well-being, whereas an individual's psychological well-being affects their own personal earnings. That only household income per capita affects psychological well-being and not own income is an assumption that I make throughout the analysis in this

[16] Income and expenditure numbers are adjusted for inflation and are in November 2014 prices.

paper.[17] I represent the relationship between income and psychological well-being with the following system of equations:

$$y_{i,t} = f(D_{i,t}, y_{i,t-1}, \boldsymbol{x}_{i,t}) + \nu_i + e_{i,t}$$

$$D_{i,t} = g(h_{i,t}, D_{i,t-1}, \boldsymbol{x}_{i,t}) + \rho_i + u_{i,t}$$

where $y_{i,t}$ is individual income, $D_{i,t}$ is a measure of psychological well-being, and $h_{i,t}$ is household income per capita for individual i in time t which is a function of an individual's income.[18] In this analysis I consider only linear specifications for $f(.)$ and $g(.)$; ν_i and ρ_i are individual fixed effects; and $e_{i,t}$ and $u_{i,t}$ are the unobserved error terms for their respective equations. $\boldsymbol{x}_{i,t}$ is a vector of time varying individual characteristics for individual i at time t. While the focus of this paper is not on the dynamics of income and psychological well-being, I allow for state dependence in the underlying process by having lagged levels of personal income ($y_{i,t-1}$) and psychological well-being ($D_{i,t-1}$) as explanatory variables in the equations.

To outline and justify my estimation strategy, I present a simple linear form of the above system of equations:

$$y_{i,t} = \beta_0 + \alpha_1 D_{i,t} + \beta_1 y_{i,t-1} + \Gamma \boldsymbol{x}_{i,t} + \nu_i + e_{i,t}$$

$$D_{i,t} = b_0 + a_1 h_{i,t} + b_1 D_{i,t-1} + \Theta \boldsymbol{x}_{i,t} + \rho_i + u_{i,t}$$

To control for the individual fixed effects v_i and ρ_i that might be important determinants of both income and psychological well-being, I use the first-differenced version of both equations

[17] This assumption is nontrivial. However, the results in Appendix C (Table A5) suggest that the data does not contradict this assumption. Including both individual income and household income per capita as regressors for psychological well-being yields statistically insignificant results for individual income, even when the sample is restricted to economically active individuals. This is also the case when using other proxies for economic well-being such as food expenditure and a wealth index.

[18] This can be represented with a third equation $h_{i,t} = k(y_{i,t}, X_{i,t}) + \theta_i + \epsilon_{i,t}$, where $k(.)$ is an unknown function, θ_i is an individual fixed effect and $\epsilon_{i,t}$ is an unobserved error term. I do not estimate this equation as it is outside of the scope of this analysis.

which results in the following:

$$\Delta y_{i,t} = \alpha_1 \Delta D_{i,t} + \beta_1 \Delta y_{i,t-1} + \Gamma \Delta \boldsymbol{x}_{i,t} + \Delta e_{i,t} \tag{1}$$

$$\Delta D_{i,t} = a_1 \Delta h_{i,t} + b_1 \Delta D_{i,t-1} + \Theta \Delta \boldsymbol{x}_{i,t} + \Delta u_{i,t} \tag{2}$$

In this system of equations, I am interested in estimating the coefficients of four endogenous variables, namely α_1, β_1, a_1, and b_1. By considering each single equation separately, panel data methods suggests that, assuming $e_{i,t}$ and $u_{i,t}$ are serially uncorrelated, the lagged levels $y_{i,t-2}, y_{i,t-3}, ...$ and $D_{i,t-2}, D_{i,t-3}, ...$ may be used as instruments to estimate the parameters of the equation (1), while $h_{i,t-2}, h_{i,t-3}, ...$ and $D_{i,t-2}, D_{i,t-3}, ...$ may be used to estimate equation (2).

I extend this panel data method to estimate a system of simultaneous equations. I show below that the assumptions on $e_{i,t}$ and $u_{i,t}$ required for consistent estimation of the coefficients with four waves of panel data can be weaker than the sequential exogeneity often assumed when using lagged levels as instruments for first differences (Arellano & Bond, 1991; Bond, 2002). To estimate the above system of equations, and given that the NIDS dataset has four waves of data, I first use the following instruments matrix:

$$Z^A_{i,t} = \begin{pmatrix} D_{i,t-2} & D_{i,t-3} & y_{i,t-3} & 0 & 0 & 0 \\ 0 & 0 & 0 & D_{i,t-3} & h_{i,t-2} & h_{i,t-3} \end{pmatrix} = \begin{pmatrix} {z^1_{i,t}}' & \mathbf{0} \\ \mathbf{0} & {z^2_{i,t}}' \end{pmatrix}$$

where $z^1_{i,t} = \begin{pmatrix} D_{i,t-2} & D_{i,t-3} & y_{i,t-3} \end{pmatrix}$ – the vector of instruments for equation (1) – and $z^2_{i,t} = \begin{pmatrix} D_{i,t-3} & h_{i,t-2} & h_{i,t-3} \end{pmatrix}$ – the vector of instruments for equation (2). The assumptions required for matrix $Z^A_{i,t}$ to provide moment conditions to consistently estimate the system of equations are:

$$E\left[e_{i,t} \mid y_{i,t-2}, y_{i,t-3}, \ldots; D_{i,t-1}, D_{i,t-2}, \ldots; \boldsymbol{x}_{i,t}, \boldsymbol{x}_{i,t-1}, \ldots\right] = 0 \tag{A1}$$

and

$$E\left[u_{i,t} \mid h_{i,t-1}, h_{i,t-2}, \ldots; D_{i,t-2}, D_{i,t-3}, \ldots; \boldsymbol{x}_{i,t}, \boldsymbol{x}_{i,t-1}, \ldots\right] = 0 \tag{A2}$$

Proposition. *If assumptions A1 and A2 hold, then the matrix of instruments $Z_{i,t}^{A}$ implies moment conditions that identify the coefficients of the system of equations (equations (1) and (2)).*

The proof is straightforward and shown in Appendix A. Provided A1 and A2 hold, the matrix of instruments $Z_{i,t}^{A}$ implies the following moment conditions:

$$E\left(Z_{i,t}^{A\prime} U_{i,t}\right) = \mathbf{0}$$

Simulation results verify that under an error structure that satisfies assumptions A, using a two-step GMM and instruments matrix $Z_{i,t}^{A}$ leads to consistent estimates of the coefficients α_1, β_1, a_1, and b_1.[19]

For A1 and A2 to hold, the error term of each equation may not be correlated with $t-2$ lagged values of its own dependent variable and $t-1$ lagged values of the simultaneous variable. However, the simultaneity of the equations inherently implies that both error terms cannot be serially correlated. After controlling for state dependence (through the lagged dependent), individual fixed effects, and observable time varying characteristics, the remaining unobserved errors may not be correlated across time.[20] The time between waves in the NIDS dataset is two years which makes this assumption more plausible. Simulations illustrate the bias that first order serial correlation in each of the error terms would cause. It is worth noting that the bias caused by serial correlation in the error terms is evident only when there is simultaneity in the model; when there are no effects that leads to simultaneity (α_1 and a_1 are equal to zero), the specification will consistently estimate these coefficients

[19] Simulation results are available in Appendix B

[20] Effectively, this assumption means that a shock to income in one period can affect income next period through state dependence, but it cannot affect the likelihood of shocks in the next period. Similarly for shocks to psychological well-being.

to be zero.[21]

Throughout the rest of the paper, the main results are based on the assumption that A1 and A2 hold. I refer to these as set of assumptions A. I also present results that I estimate using the moment conditions implied by the following instruments matrix:

$$Z_{i,t}^{B} = \begin{pmatrix} D_{i,t-3} & y_{i,t-3} & 0 & 0 \\ 0 & 0 & D_{i,t-3} & Y_{i,t-3} \end{pmatrix}$$

The following less restrictive set of assumptions – which I refer to as assumptions B – are required for $Z_{i,t}^{B}$ to imply the moment conditions $E\left(Z_{i,t}^{B\prime}U_{i,t}\right) = \mathbf{0}$:

$$E\left[e_{i,t} \mid y_{i,t-2}, y_{i,t-3}, \ldots; D_{i,t-2}, D_{i,t-3}, \ldots; \boldsymbol{x}_{i,t}, \boldsymbol{x}_{i,t-1}, \ldots\right] = 0 \qquad \text{(B1)}$$

and

$$E\left[u_{i,t} \mid Y_{i,t-2}, Y_{i,t-3}, \ldots; D_{i,t-2}, D_{i,t-3}, \ldots; \boldsymbol{x}_{i,t}, \boldsymbol{x}_{i,t-1}, \ldots\right] = 0 \qquad \text{(B2)}$$

Proposition. *If assumptions B1 and B2 hold, then the matrix of instruments $Z_{i,t}^{B}$ implies moment conditions that identify the coefficients of the system of equations (equations (1) and (2)). In addition, $Z_{i,t}^{B}$ also provides moment conditions to identify the coefficients under the more restrictive set of assumptions A.*

The proof is shown in Appendix A and follows the same logic as the proof for $Z_{i,t}^{A}$. Removing the lagged $t-2$ level variables from the matrix of instruments allows for less restrictive assumptions on the error terms. In addition, a matrix of instruments that provides consistent estimates under less restrictive assumptions on the error terms will also do so under more restrictive assumptions.

Under B1 and B2, the error terms may be serially correlated across one time period. Assuming income shocks to be correlated over one time period is common in the literature on income dynamics and state dependence of income and employment (Guvenen, 2007; Magnac,

[21] This can be seen in simulation results shown in Appendix B Table A2 and A3.

2000; Meghir & Pistaferri, 2004).[22] Moreover, the error terms $e_{i,t}$ and $u_{i,t}$ may be correlated with $u_{i,t-1}$ and $e_{i,t-1}$, respectively. Throughout the results section below, I show, where appropriate, estimates based on both set of assumptions A and B. The estimates do not differ significantly throughout and the results from assumptions B indicate that the main results are robust to less restrictive assumptions. A Hausman-type test does not reject that the estimates using the two instruments matrices are the same.[23] This suggests, albeit indirectly, that the error terms are not strongly serially correlated. Although the dataset has four waves of data, after taking the first difference and using lagged levels $t-2$ and $t-3$ as instruments, I effectively have one observation per individual. Thus, I cannot directly test for serial correlation. However, when using $Z^A_{i,t}$, if a test of overidentifying restrictions rejects the validity of the instruments, it would be another indirect evidence of serial correlation; the validity of the instruments is not rejected in any of the results presented in the rest of the paper.

5 Results

5.1 System GMM

In Section 4, I consider a simple linear version of the system of equations to illustrate the estimation strategy. The results presented in the rest of the paper are mainly estimates of the following more flexible system of equations:[24]

$$\Delta y_{i,t} = \alpha_1 \Delta D_{i,t} + \beta_1 \Delta y_{i,t-1} + \Gamma \Delta \boldsymbol{x}_{i,t} + \Delta e_{i,t} \tag{3}$$

[22] The time periods considered are often of higher frequency. The time between each wave in this paper is two years – and income is reported for the past month – making serial correlation less likely.

[23] Neither regression gives results that can be realistically described as fully efficient, thus when testing for the statistical significance of the difference of the estimates (A Hausman-type test), I estimate variance of the difference using a bootstrap.

[24] With this system of equations I add a quadratic term of $h_{i,t}$. Intuitively, changes in income may affect psychological well-being at a decreasing rate. The assumptions required for validity do not change. I add quadratic terms of the instrumental variables to the instrument vectors. The results are robust to higher order specifications.

$$\Delta D_{i,t} = a_1 \Delta h_{i,t} + a_2 \Delta h_{i,t}^2 + b_1 \Delta D_{i,t-1} + \Theta \Delta \boldsymbol{x}_{i,t} + \Delta u_{i,t} \tag{4}$$

I estimate the above system of equation with the following instruments matrix:

$$Z_{i,t}^A = \begin{pmatrix} D_{i,t-2} & D_{i,t-3} & y_{i,t-3} & h_{i,t-3} & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & D_{i,t-3} & h_{i,t-2} & h_{i,t-2}^2 & h_{i,t-3} & h_{i,t-3}^2 \end{pmatrix}$$

The two-step GMM results for the whole sample are shown in Table 2. The results in column 1 show that changes in CES-D do not, on average affect, individual income. Changes in household income per capita, on the other hand, do have a statistically significant impact on CES-D.

Column 2 shows the estimates using the following instruments matrix:

$$Z_{i,t}^B = \begin{pmatrix} D_{i,t-3} & y_{i,t-3} & h_{i,t-3} & 0 & 0 & 0 \\ 0 & 0 & 0 & D_{i,t-3} & h_{i,t-3} & h_{i,t-3}^2 \end{pmatrix}$$

This instruments matrix requires the less restrictive assumptions B that allow for serial correlation in the error terms across 1 time period. The results in column 2 show similar patterns. A Hausman-type test shows that the differences in the estimates in column 1 and 2 are not statistically significant suggesting that there is no serial correlation in the error terms. In addition, testing for overidentifying restrictions provides Hansen J-test statistics that do not reject the validity of the instruments. This is the case for all of the GMM results presented in the rest of the paper. All standard errors shown in the tables are cluster robust standard errors clustered at the PSU level.[25]

The system GMM results for the whole sample show a negative yet statistically insignificant estimate of the effect of CES-D on individual income. In the next section, I exclude the elderly and explore the nonlinearities suggested in the literature on depression and CES-D discussed in Section 2.1. On the other hand, the two system GMM results show

[25] PSUs are defined geographic areas based on the 2001 census in South Africa based on which the sampling for NIDS took place.

similar effects of income on depressive symptoms whereby a ZAR 250 increase in household income per capita decreases the CES-D scale (lowers depressive symptoms) by about 0.85 points on average.[26] The quadratic term is statistically significant suggesting that increases in income decrease depressive symptoms at a decreasing rate. This side of the simultaneous equations, the effect of income on psychological well-being, is analyzed in more detail in Section 5.3.

5.2 The Impact of CES-D on Individual Income

5.2.1 General Results

To further study the effect of depressive symptoms on individual income, I focus specifically on equation (3) from the system of equations above:

$$\Delta y_{i,t} = \alpha_1 \Delta D_{i,t} + \beta_1 \Delta y_{i,t-1} + \Gamma \Delta \boldsymbol{x}_{i,t} + \Delta e_{i,t} \tag{3}$$

I restrict the sample to working age adults between ages 22 and 60,[27] and I use the same two-step system GMM as above to estimate the coefficients. Table 3 presents the estimates for equation (3) using both instruments matrices $Z^A_{i,t}$ and $Z^B_{i,t}$. The difference between column 1 and 2 is the inclusion of the lagged individual income in column 2. The point estimates are different suggesting that failing to account for the state-dependent nature of income biases the results. A similar and more stark pattern is evident when using instruments matrix $Z^B_{i,t}$. The results indicate that, among working age individuals, increases in depressive symptoms decrease individual income. The magnitude of this effect is large as average monthly income among employed individuals is ZAR 4,316.[28]

The psychology literature on the CES-D scale indicates that the score of 10 or above

[26] Mean and median of household income per capita are ZAR 2,242 and ZAR 1,024, respectively. This translates to USD 199 or USD 418 adjusted for purchasing power. Mean CES-D score is 7.1 and the standard deviation is 4.2.

[27] Labor force participation drops sharply to under 20% after age 60.

[28] Overall mean of monthly income among working age individuals is ZAR 2,779.

suggests that a person may be suffering from what would be clinically diagnosed as depression. In South Africa specifically, a recent study by Baron et al. (2017) finds that, on average, a threshold of 11 is more appropriate among the South African population. Changes within the lower range of the score (0-8) track changes in psychological well-being, but these changes may not affect an individual's economic behavior in a meaningful way. While the CES-D may be viewed as a continuum of psychological well-being (Siddaway et al., 2017; Wood et al., 2010), the functional impairment and/or other symptoms that could affect an individual's income may not be evident until an they are experiencing depression. In the rest of this section, I analyze the data with the CES-D score of 10-12 in mind as a threshold where large impacts may be present.

To investigate whether there are significant nonlinearities in the data, I systematically restrict the sample to individuals who in either wave 3 or 4 (or both) were above a certain threshold CES-D score. For example, at the threshold of 7, I restrict the sample to contain only individuals who had a CES-D score of 7 or more in wave 3, wave 4, or both. This excludes those who did not experience enough psychological distress to attain scores above the threshold in either waves. Table 4 shows the results for thresholds ranging from 7 to 12. The results suggest that there may be nonlinearities in the effect of changes in CES-D on income as the point estimates are larger for individuals who report CES-D scores closer to the depression thresholds. For those who cross or are always higher than the threshold of 10 or 11, the results predict that a 1-point increase in CES-D score decreases individual income by ZAR 400-500, more than double the estimated overall affect in Table 3.

To test the robustness of these effects, I split individual income into two categories: earned income composed of wages, income from day labor and self-employment, and other income which, in the NIDS sample, constituted mainly income from rent, government grants, and other forms of assistance. In theory, depression should mainly affect earned income and should not affect other forms of income. I rerun the same specification from Table 4 and find that the results for earned income, presented graphically in Figure 3, mirror the results for individual income in Table 4. On the other hand, the estimates for other income are small and statistically insignificant indicating that changes in CES-D do not, as suspected, affect other income.

5.2.2 The Marginal Effect Curve

The regressions and figure above indicate the existence of nonlinearity in the marginal effect of CES-D on income. A 1-point change in the CES-D score when an individual has CES-D score of 3 may be different from when the baseline CES-D score is 9, for example. To capture this heterogeneity and estimate the marginal effect at each baseline CES-D score, an ideal dataset would have a very large number of observations at each baseline (wave 3) CES-D score and all individuals would experience a change of 1 or -1 in their CES-D score between waves 3 and 4. Applying the same specification as above for all the individuals for a sample restricted to individuals at each baseline CES-D score would estimate the marginal effect of CES-D on individual income at each CES-D score.[29] Applying this exactly in the NIDS dataset leads to very small sample sizes. However, increasing the bandwidth to 1 in local linear regression terms,[30] and restricting the sample to individuals who experience changes less than or equal to the absolute value of 4 in their CES-D score between wave 3 and 4 (instead of 1)[31] gives sample sizes that allow me to estimate the marginal effects. I view this estimation approach as a type of local linear regression adapted to a first differenced equation with a discrete variable.

The results of this estimation method are illustrated in Figure 4. While psychologists offer a clear hypothesis that changes in CES-D matter mainly in the region around the score of 10, I present a conservative Bonferroni corrected confidence interval to control for the

[29] This implicitly assumes that individuals at different levels of baseline CES-D are identical on all characteristics except baseline CES-D score and income.

[30] In this discrete variable case, when estimating the marginal effect at CES-D = 5 in wave 3, I would include individuals who have CES-D of 4,5, or 6 in wave 3. Observations where baseline CES-$D_3 = j \pm 1$ were weighted at 1/3 that of j. The results are robust to a range of different weighting specifications.

[31] Results (in Appendix C Table A6) in which the sample is restricted to individuals who experience smaller and larger changes (3 and 5) exhibit a similar pattern around the threshold of 10, but have slightly different point estimates.

family-wise error rate (in red).[32] The estimates suggest that when an individual is at the threshold of 10, a 1-point increase in their CES-D score decreases income by 441 ZAR. This estimate is significant at the 1% level even after a Bonferroni adjustment to the p-value. The model estimates slightly smaller marginal effects at CES-D scores 11, 12, and 13 that are statistically significant at the 5% level. Moreover, the largest estimate is at the CES-D score of 9. The marginal effect of an increase in CES-D of 1 is estimated to -529 ZAR. If I consider an individual with an average CES-D score of 7 in period 3, an almost 1 SD increase in their CES-D (4 points) is estimated to decrease their individual income by ZAR 971 or about 0.25 SD on average. The average income for an employed individual with CES-D equal to 7 is ZAR 4,250; the estimates predict that a 4-point increase in CES-D score would decrease the individual's income by nearly 23%.[33]

While overall changes in CES-D do seem to, on average, affect an individual's income in a statistically significant way, the results presented in this section suggest that there are significant nonlinearities. Depression is increasingly likely among individuals with CES-D scores of 10 and above. The results above show that for those who experience that threshold, changes in CES-D score have large impacts on their income; the results suggest that exogenously decreasing the depressive symptoms of working age individuals with CES-D greater than or equal to 10 by one standard deviation[34] would decrease extreme poverty rates in South Africa by nearly four percentage points (from 20.8% to 16.9%).

5.2.3 Mechanisms and Other Effects

Table 5 presents results that investigate some of the possible mechanisms through which changes in CES-D might affect individual income, in addition to other consequences of increased depressive symptoms. All the results in Table 5 are estimated using a single

[32] To obtain the point estimates mapped out in Figure 4, I run 13 separate regressions. I update the confidence intervals to correct for multiple testing.

[33] Just over 20% of individuals with CES-D scores of 6,7, or 8 in wave 3 experience a change greater than or equal to 4 between wave 3 and wave 4.

[34] Interventions such as cognitive behavioral therapy often achieve changes that are larger on average.

equation GMM specification for the variable of interest, $m_{i,t}$, that is similar to the system specification above. The estimated equation is the following:

$$\Delta m_{i,t} = \zeta_1 \Delta D_{i,t} + \zeta_2 \Delta m_{i,t-1} + \zeta_3 \Delta \boldsymbol{x}_{i,t} + \Delta \epsilon_{i,t}$$

using the the instruments vector $z^m_{i,t} = \begin{pmatrix} D_{i,t-2} & D_{i,t-3} & m_{i,t-3} \end{pmatrix}$. The estimates in column 1 of Table 5 suggest that one of the likely mechanisms through which an increase in CES-D decreases income is through decreased labor force participation. The results predict that a 1-point increase in CES-D scale results in a 7.1 percentage-point decrease in the likelihood of labor force participation. The point estimates for employment (given participation in the labor force) and for hours worked (given employment) in column 2 and 3, respectively, show similar negative effects of increases in CES-D.

The results in column 4-6 of Table 5 look at other indirect mechanisms. Estimates in column 4 show that after controlling for household income and food expenditure, an increase in CES-D significantly increases the share of expenditure that goes to temptation goods;[35] a 1-point increase in CES-D increases the share of temptation good spending by 0.69 percentage points. Compared to a base level of 4.2%, this means that temptation good spending increases by nearly 16%. This is in line with the prediction of the theoretical model of De Quidt and Haushofer (2016) which states that depression would lead to greater consumption of temptation goods.

Moreover, using a social cohesion index (for individuals) constructed in a manner similar to the index constructed by Burns, Njozela, and Shaw (2016) for South Africa (using the same NIDS data), I find that increases in depressive symptoms as measured by increases in CES-D scores lower perceptions of social cohesion for an individual in a statistically significant way (column 5). This index is constructed using questions about trust, perceptions of inequality, and fairness; this result suggests that the impact of psychological well-being may have wide social implications.

[35] I define cigarettes, alcohol, gambling, and store-bought sweets as temptation goods.

Finally, column 6 shows that changes in CES-D change an individual's perception about the future. Higher CES-D scores cause lower levels of hopefulness about an individual's future income and social status. This finding is expected as low levels of hopefulness and negative perceptions of the future are symptoms of depression.

Further analysis of these relationships (Figures A2 and A3 in Appendix D) shows that, while not always statistically significant (possibly due to small sample sizes), the effect of CES-D on some of these variables exhibits a similar nonlinear pattern to the one on income. For those who pass or always exceed the threshold of 10, an increase in their CES-D score decreases the likelihood of being economically active, employment rates, hours worked, and increases the share of temptation good spending. However, measures of social cohesion and hopefulness do not seem to exhibit this pattern.

The results from this section show that psychological well-being has important economic consequences. For the nearly 30% of the sample with a CES-D score of 9 or above (as seen in Figure 1), changes in psychological well-being can have a significant economic impact.

5.3 The Impact of Income on Psychological Well-Being

The results from Section 5.1 show that changes in income affect psychological well-being for the average individual in the sample. To further explore this impact, I focus on equation (4) in the system of equations above:

$$\Delta D_{i,t} = a_1 \Delta h_{i,t} + a_1 \Delta h_{i,t}^2 + b_1 \Delta D_{i,t-1} + \Theta \Delta \boldsymbol{x}_{i,t} + \Delta u_{i,t}$$

When looking at the impact of household income per capita, I use the system estimation strategy used in Section 5.1. For other measures of economic well-being, namely food expenditure per capita and a household wealth index, I use a similar single equation estimation strategy and an equivalent vector of instruments to estimate the coefficients of the equation above.[36]

Table 6 presents the estimates for different variations of equation (4) using two-step GMM estimation. Columns 1-3 present results for the vector of instruments $z_{i,t}^{A}$ that provides consistent estimates under assumptions A. The results show that for three different measures of economic well-being – household income per capita, food expenditure per capita, and a household wealth index – a change in economic well-being affects the CES-D score in a statistically significant way. The estimates in column 1 and 4 are the same estimates from Table 2. The model suggests a decreasing marginal effect of household income per capita due to the statistically significant quadratic term. Table 8 shows results using the natural log of household income per capita. The model estimates that a 10% increase in household income per capita decreases an individual's CES-D score by 0.206 points.

To test the robustness of these results, I replace household income with other measures of economic well-being, namely food expenditure and wealth. The results are similar in signs and statistical significance for both food expenditure per capita and the wealth. The estimates in Table 6 predict that a ZAR 100 (mean food expenditure per capita is nearly ZAR 400) decrease in food expenditure increases CES-D score by 0.8 points. Also a large 1-SD increase in wealth measured by the wealth index is predicted to decrease CES-D scores by near 3.2 points.[37]

Columns 4-6 show estimates for the econometric specification that requires less restrictive assumptions. The results are similar to those in columns 1-3 which demonstrates that the results are robust to specifications that allow for serial correlation with different measures of economic well-being.

Intuitively, it seems as though the impact of income on psychological well-being may

[36] I consider a quadratic specification for impact of food expenditure per capita (fe) on CES-D, and I use $z_{i,t}^{Afe} = \begin{pmatrix} fe_{i,t-2} & fe_{i,t-2}^{2} & fe_{i,t-3} & fe_{i,t-3}^{2} & D_{i,t-3} \end{pmatrix}$ under assumptions A and $z_{i,t}^{Bfe} = \begin{pmatrix} fe_{i,t-3} & fe_{i,t-3}^{2} & D_{i,t-3} \end{pmatrix}$ under assumptions B. When considering the wealth index (w), I use $z_{i,t}^{Aw} = \begin{pmatrix} w_{i,t-2} & w_{i,t-3} & D_{i,t-3} \end{pmatrix}$ under assumptions A and $z_{i,t}^{Bw} = \begin{pmatrix} w_{i,t-3} & D_{i,t-3} \end{pmatrix}$ under assumptions B.

[37] In another paper that uses the same data and a similar econometric specification and data from several countries including South Africa, I find that measures of subjective well-being, namely life satisfaction and reported happiness are positively affected by increases in income.

be larger for the poor. To test this, I restrict my sample to the poorest 54% and 20% - which Leibbrandt et al. (2014) suggest is the poverty and extreme poverty head count percentages in South Africa. The results in Table 7 clearly show larger point estimates for the poor.

The magnitude of the estimated effects of changes in household income on psychological well-being are in line with other experimentally estimated impacts. In Haushofer and Shapiro (2016), the unconditional cash transfer of nearly PPP $45 per capita targeting the poor led to an additional increase in revenue of nearly $16 on average. The treated households showed an overall decrease in nearly 1.2 in their CES-D20 score. Back-of-the-envelope calculation and an equivalent PPP adjustment shows that a similar increase in income among the poorest 20% in South Africa would lead to nearly 0.64 reduction in CES-D. Noting that Haushofer of Shapiro use CES-D20 in their analysis and abstracting away from the complexity of predicting CES-D20 scores with CES-D10, the estimates in this analysis on the impact of household income per capita on CES-D are similar in size.

5.3.1 Alternative Instrument

To check for the robustness of the estimates of the impact of income on psychological well-being using the panel GMM approach, I use an alternative plausible instrument for household income. Between 2008 (wave 1) and 2012 (wave 3), the government of South Africa expanded the eligibility age for the child grant program from 14 to 16 in early 2010, and from 16 to 18 in 2012. This grant is means tested on the income of the caregiver and has high rates of take up (Woolard, Buthelezi, & Bertscher, 2012). I construct a variable that counts the number of children per household that were eligible due to each expansion and use this as an instrument for household income per capita. The results are shown in column 7 of Table 6. The estimates again predict that an increase in income decreases an individual's CES-D score which reflects a decrease in depressive symptoms. Moreover, the point estimates are close in magnitude to the point estimates calculated using the panel GMM method above.

5.3.2 Heterogeneity

The results for the poor subsample suggest that there may be heterogeneity in the effect of income on psychological well-being based on the individual's baseline level of economic well-being. Intuitively, this makes sense: a 100 ZAR increase in household income per capita for a wealthy family may not have the same effect on psychological well-being as it would for individuals in a poor family. Even when considering percent changes in household income, a 10% increase in income for a upper middle income household whose basic material needs are mostly taken care of might not be affected psychologically as much as a poor household struggling to make ends meet. This can be seen in Table 8 where the point estimates for the effect of changes in the log of income on CES-D are larger among the poor.

To systematically analyze these heterogeneous effects, I use an estimation strategy that mirrors the one I use above to estimate the nonlinear impact of CES-D on income. However, I use discrete household income per capita deciles to define the samples for the estimated regressions. Again, I correct the confidence intervals for multiple testing using a conservative Bonferroni approach. I present results for both absolute changes in income and food expenditure per capita in Figure 5. It is clear from the results that the point estimates of the effect of changes in income on psychological well-being is larger for the poorer population. For the poorest three deciles, a change in income affects their CES-D score in statistically significant ways. Changes in food expenditure show significant impacts on CES-D for the poorest four deciles. The effect of changes in income and food expenditure on psychological well-being are not statistically significant for upper household income deciles.[38] It may be that after basic material needs are met, additional income does not affect psychological well-being. Figure 6 shows the results for percent changes in household income per capita and food expenditure per capita which show similar results, however, the magnitude of the marginal effect of a percent change in income is relatively constant for the first three deciles.[39]

[38]This may be due to smaller sample sizes, however, the point estimates are closer to zero.

[39]While changes in income among individuals in the upper income deciles does not affect psychological well-being, this does not mean that it does not change their subjective well-being. While they are correlated, life

The results in this section demonstrate the effect of income and other measures of economic well-being on psychological well-being as measured by CES-D. These effects are especially pronounced for the poorer part of the sample. This suggests that a shock to income may have significant psychological consequences for vulnerable portions of the population.

6 Implications for Income Dynamics and Poverty

Above, I estimate a system of simultaneous and dynamic equations that indicate the extent to which psychological well-being is intertwined with income and poverty. In this section, I show that psychological well-being may play an important role in the dynamics of income and the persistence of poverty. In section 6.1, I borrow from the structural vector auto-regression literature and show how the bi-directional relationship exacerbates the impacts of shocks to either variable over time. In section 6.2, I use simulations to illustrate the impact this relationship can have on the persistence of poverty. Finally in section 6.3, I test for poverty traps using the method developed by Arunachalam and Shenoy (2017) on two subsamples: those with high overall levels of psychological well-being and those who report low levels of psychological well-being.

6.1 Impulse Response Function

In this section, I borrow from the structural vector auto-regression literature to look at how the estimated dynamic and bi-directional relationship between income and psychological well-being alters the way shocks in a certain time period affect the two variables in the future. While in the system of equations above, I distinguish between household income and individual income, in this section, I abstract away from this distinction and I treat them as

satisfaction and happiness are different from mental health and the impact of income on them is heterogeneous in a different way than for CES-D. In another paper focused specifically on income and measures of subjective well-being, I show that changes in income causes changes in measures of subjective well-being change for individuals in most of the baseline income and wealth distribution (Alloush, 2018). It may be that when basic needs are not satisfied, psychological well-being improves, but after they are, psychological well-being isn't necessarily affected by income but measures of subjective well-being are.

the same variable: first I consider a single person household where the two are by default equalized, and then I generalize the result by tempering the effect of changes in CES-D on household income and reducing it to 0.5 times the estimated effect on individual income.[40] In addition, since I am considering small marginal changes, I ignore the estimated quadratic term. The simplified system of equations is the following:

$$\Delta h_{i,t} = \alpha_1 \Delta D_{i,t} + \beta_1 \Delta h_{i,t-1} + \Delta e_{i,t}$$

$$\Delta D_{i,t} = a_1 \Delta h_{i,t} + b_1 \Delta D_{i,t-1} + \Delta u_{i,t}$$

I can represent the above equations in the following matrix form:

$$AY_{i,t} = BY_{i,t-1} + \epsilon_{i,t}$$

where $Y_{i,t} = \begin{pmatrix} \Delta h_{i,t} & \Delta D_{i,t} \end{pmatrix}'$, $\epsilon_{i,t} = \begin{pmatrix} \Delta e_{i,t} & \Delta u_{i,t} \end{pmatrix}'$, $A = \begin{pmatrix} 1 & -\alpha_1 \\ -a_1 & 1 \end{pmatrix}$ and $B = \begin{pmatrix} \beta_1 & 0 \\ 0 & b_1 \end{pmatrix}$, which can be rewritten as:

$$Y_{i,t} = A^{-1}BY_{i,t-1} + A^{-1}\epsilon_{i,t}$$

A Wold decomposition of the above equation gives the following:

$$Y_{i,t} = \sum_{j=0}^{\infty} (A^{-1}B)^j A^{-1} \epsilon_{i,t-j}$$

The above decomposition allows me to look at the effects of shocks (in ϵ) on $Y_{i,t}$ over

[40] This is the lower bound of the 95% confidence interval of the estimated effect of changes in individual income on household income per capita (these results are shown in Table A9 in the Appendix).

time. For example, a shock in income in $t-j$ has the following effect on $Y_{i,t}$:

$$\frac{\delta Y_{i,t}}{\delta e_{i,t-j}} = (A^{-1}B)^j A^{-1} e_1$$

where $e_1 = \begin{pmatrix} 1 & 0 \end{pmatrix}'$. Figure 7 shows the plot of the impulse response function of a negative shock to income over time in this system of equations compared to an AR(1) process for a household with a single individual and Figure 8 shows the general result. This relationship accentuates the effect of the initial shock but also has an added impact over time. Calculating the overall effect of a shock to income (for the general result) shows that this relationship nearly doubles the total long-term impact of a shock.[41] The dynamics of income and psychological well-being are similarly affected by shocks to either one: Figure A4 in the Appendix illustrates how shocks to either income or psychological well-being affect both variables and how these shocks are exacerbated both initially and over time.

6.2 Poverty Dynamics: Simulations

Section 6.1 suggests that the bi-directional relationship can exacerbate the effects of shocks which may help explain low levels of resilience among some. Can the this relationship also help explain the persistence poverty? The results suggest a strong feedback loop for the poor with low levels of psychological well-being. To illustrate the implications of the relationship on poverty dynamics, I use the estimated system of dynamic equations to simulate income and CES-D over time.[42] I independently and randomly draw income and CES-D values at time 0 with means and variances reflecting those of individual income and CES-D in the NIDS dataset. At time zero, CES-D score is independent of income and the cumulative

[41] This is achieved by adding the infinite sum of $\frac{\delta Y_{i,t+j}}{\delta e_{i,t}}$. $\sum_{j=0}^{\infty}(A^{-1}B)^j A^{-1}e_1$ which is a geometric series and converges to $(I - A^{-1}B)^{-1}A^{-1}e_1$.

[42] In these simulation, I implicitly assume that the path of income over time is not changing, and extrapolating what happens over a longer period of time using estimates from 1 time period: a first difference and lagged instruments effectively mean that I use 1 observation per individual. In addition, for simplicity I assume that there are no intra-household responses to changes in individual income and that all households face the same income path.

distribution functions (CDFs) of income across the two groups (low versus high CES-D scores) are identical (shown on the left side of Figure 9.A). If psychological well-being played no role in determining income (the counterfactual), the two CDFs would look identical over time; this is illustrated in Figure 9.A (plot on the right) where I show the CDFs of income after five time periods (or 10 years) simulated using the estimated equations without the simultaneous causality.[43]

However, simulating the model with the full relationship estimated above, it is clear that those who randomly start in period 0 with high levels of CES-D are worse off after five time periods (Figure 9.B). Focusing on the poverty reference line, it is clear that after five time periods, poverty rates among those starting with high levels of CES-D is nearly 10 percentage points higher than those who start with low levels of CES-D. This difference is only evident in the lower part of the income distribution. While not necessarily implying a poverty trap, this suggests that the randomly assigned initial CES-D scores play an important role in determining poverty levels in the future.

In Section 6.1, the impulse response analysis showed that the feedback loop between income and psychological well-being is expected to worsen the impact of an income shock in time 0 and over time. I illustrate the implications of this on poverty levels in Figure 10 with CDFs of income after shocks at time 0 to either income (Figure 10.A) or psychological well-being (Figure 9.B). In this case, the counterfactual to consider is the income paths shown in Figure 9.B, where psychological well-being interacts with income but there are no shocks in time 0. These shocks increase overall poverty rates, however, they also increase the difference in poverty rates between the two groups over time. Five time periods after a 20% income shock, the poverty rate among those who experience the shock with high levels of CES-D is nearly 20% points higher than the others. In the NIDS sample, over 30% of individuals in the lower half of the household income per capita distribution have a CES-D score of nine or above. The results suggests that an across-the-board shock to either income or psychological

[43] As noted earlier, the time difference between waves in the NIDS dataset is 2 years.

well-being affects some individuals – the poor with low levels of psychological well-being (approximately 18% of the NIDS sample) – disproportionately. This analysis identifies a group which is slower to exit poverty but also whose resilience to shocks may be hampered.

These simulations suggest that poverty and high CES-D scores predict a higher likelihood of being poor in the future. I test whether this is evident in the NIDS data by running a simple linear regression for predictors of poverty in wave 4. In addition to a battery of controls, I use dummy variables for poverty and high CES-D scores in wave 1, and their interaction as explanatory variables. I find that poverty in period 1 predicts poverty in period 4. Moreover, the interaction of poverty and high CES-D scores in wave 1 predict a higher likelihood of poverty in wave 4 in a statistically significant way (Appendix Table A9).

6.3 Poverty Traps

Do these effects create a poverty trap?[44] In general, micro-level poverty traps can occur when individuals or households experience some self-reinforcing behavior or mechanism that causes poverty to persist. Thus, a feedback loop involving income with large enough effects could lead to a poverty trap. The results above show that for those in the lower part of the income distribution, changes in economic well-being affect their psychological well-being in significant ways. At the same time, the results indicate that changes in psychological well-being near the depression threshold lead to significant changes in individual income and, consequently, their household income.[45] Thus, a strong feedback loop may exist for the poor experiencing low levels of psychological well-being.

To test for this, I use the method introduced by Arunachalam and Shenoy (2017).

[44]The literature on poverty traps is long and the evidence of traps is mixed and context specific. In addition, the difficulty in identifying these traps is well established. For more see Antman and McKenzie (2007); Barrett and Carter (2013); Lybbert, Barrett, Desta, and Coppock (2004); McKenzie and Woodruff (2006) among many others.

[45]Estimating the model with household income as the dependent variable (in equation (1)) instead of individual income, shows a similar pattern around the depression threshold. However, the point estimates are smaller (as would be expected when dividing individual income by household size) but also shows less statistical significance overall suggesting that there might be intra-household economic responses to a decrease in a member's income.

This method is based on the notion that households just under the poverty trap thresholds are likely to experience negative income growth as they are being pulled towards the low steady state; whereas households just above the threshold will have a lower likelihood of suffering a negative income growth and experience a pull towards the higher steady state. If no poverty trap exists, the likelihood of experiencing negative income growth increases with baseline income.

Figure 11 shows the likelihood of experience a negative income growth between wave 3 and wave 4 based on the household income per capita decile in wave 3. I split the sample into two based on the psychological well-being of the household head in wave 1 and 2. Households with heads that have low levels of psychological well-being generally have higher likelihood of experiencing negative income growth overall. In addition, the trend shows a kink at decile 6 where the likelihood of experiencing a decrease in income increases sharply and then decreases for decile 7. For the other household, the trend shows an increasing likelihood of experiencing negative income growth. While the two are not statistically different from each other, the dynamics estimated for households with heads with low psychological well-being are suggestive of a multi-equilibrium poverty trap.

7 Conclusion

This paper explores the bi-directional relationship between income and psychological well-being. Despite its importance, this relationship is understudied in economics likely because of the difficulty in establishing causality in observational data. In addition, experimental variation in improvements in psychological well-being may be achieved among very specific samples (those suffering from psychological distress who sought treatment), however, the effects are not necessarily symmetric to the effects of decreases in psychological well-being. A similar critique could be made when it comes to the impacts of negative shocks to income on psychological well-being. Recently, large-scale and high-quality panel datasets that track mental health are becoming available and these allow for the use and development of econometric methods that answer important questions. With the assumptions required to infer causality from observational data in mind, the goal of this paper is to shed light on the relationship between psychological well-being and income in the general population in a way that cannot necessarily be done with experimental studies. My hope is that the results from this paper guide and encourage future research on this topic.

The four-wave panel dataset from South Africa allows for identification using GMM. However, taking into account individual fixed effects and using $t-3$ lagged levels as instruments effectively reduces the sample to one observation per individual. This inhibits the ability to test for serial correlation, for example. Applying this GMM specification to longer panels will be a fruitful exercise in the future. With assumptions on serial correlation in mind, I estimate both causal links and find significant impacts in both directions. Using the estimates of this paper, I find that nearly 40 percent of the overall decrease in CES-D score for the sample in South Africa between 2008 and 2014 can be explained by the increase in overall food expenditure per capita.

The results of this paper add to the discussion on unexpectedly large impacts of some poverty alleviation programs. Several recent studies have documented increases in income and behavioral changes among the ultra-poor that far exceed the expected benefits of the assistance programs (for example Atkin (2011); Beaman, Duflo, Pande, and Topalova (2012)). Giving some form of aid that alters the initial circumstances of households may change behavior – such as expenditure and investment – in a way that is expected and can be explained by increases in income (direct and indirect) due to aid. But dollar for dollar, the benefits of some programs exceed even the most optimistic predictions; from a structural point of view, the relevant parameters that could explain these large changes would have to have unrealistic values. Recently, some economists have attributed these changes to *hope*. Prior to these aid programs, poor households were held back partly because of hopelessness. But aid has ostensibly given them hope, and this has translated into even better economic outcomes (Lybbert & Wydick, 2018). In this paper, I show that a related and possibly deeper mechanism may be at play here. A stable income through aid likely improves levels of psychological well-being which allows individuals to realize their capabilities and further improve their economic well-being in a way that exceeds initial expectations.

The evidence in this paper suggests that aside from being a constitutive and important outcome in itself, psychological well-being is also an instrumental one. The impact of poverty on psychological well-being may hinder an individual's ability to bounce back after an income shock or escape poverty. Understanding the impact of negative versus positive economic shocks on psychological well-being may be a fruitful future endeavor. In addition, shedding light on the mechanisms through which changes in psychological well-being affect income is important. In this paper and in De Quidt and Haushofer (2016), entering and exiting the labor force is the main mechanism. However, researchers in psychology have shown various ways different mental disorders affect preferences and even cognitive ability. Understanding these mechanisms is germane to the design of effective poverty alleviation policy.

References

Alloush, M. (2018). Economic Well-being and Happiness. *Working Paper*.

Antman, F., & McKenzie, D. (2007). Poverty traps and nonlinear income dynamics with measurement error and individual heterogeneity. *Journal of Development Studies*, *43*(6), 1057–1083.

Arellano, M., & Bond, S. (1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The Review of Economic Studies*, *58*(2), 277.

Arunachalam, R., & Shenoy, A. (2017). Poverty traps, convergence, and the dynamics of household income. *Journal of Development Economics*, *126*(December 2016), 215–230.

Atkin, D. (2011). Working for the Future: Female Factory Work and Child Health in Mexico. *Working Paper*(May).

Banerjee, A., Duflo, E., Goldberg, N., Karlan, D., Osei, R., Pariente, W., … Udry, C. (2015). A multifaceted program causes lasting progress for the very poor: Evidence from six countries. *Science*, *348*(6236), 12 60799–1– 1260799–16.

Baron, E. C., Davies, T., & Lund, C. (2017). Validation of the 10-item Centre for Epidemiological Studies Depression Scale (CES-D-10) in Zulu, Xhosa and Afrikaans populations in South Africa. *BMC Psychiatry*, *17*(1), 6.

Barrett, C. B., & Carter, M. R. (2013). The economics of poverty traps and persistent poverty: Empirical and policy implications. *Journal of Development Studies*, *49*(7), 976–990.

Beaman, L., Duflo, E., Pande, R., & Topalova, P. (2012). Female Leadership Raises Aspirations and Educational Attainment for Girls: A Policy Experiment in India. *Science*, *335*(6068), 582–586. doi: 10.1126/science.1212382

Beck, A. T. (1967). *Depression: Causes and Treatment* (1st ed.). Philadelphia: University of Pennsylvania Press.

Bolton, P., Bass, J., Neugebauer, R., Verdeli, H., Clougherty, K. F., Wickramaratne, P., … Weissman, M. (2003). Group Interpersonal Psychotherapy for Depression in Rural Uganda: A Randomized Controlled Trial. *Jama*, *289*(23), 3117–3124.

Bond, S. (2002). Dynamic Panel Data Models: A Guide to Micro Data Methods and Practice. *Portuguese Economic Journal*, *1*, 141–162.

Burns, J., Njozela, L., & Shaw, I. (2016). *Towards measuring social cohesion in South Africa.* Cape Town.

Cella, M., Dymond, S., & Cooper, A. (2010). Impaired flexible decision-making in major depressive disorder. *Journal of Affective Disorders*, *124*(1-2), 207–210.

Chatterji, P., Alegria, M., & Takeuchi, D. (2011). Psychiatric disorders and labor market outcomes: Evidence from the National Comorbidity Survey-Replication. *Journal of Health Economics*, *30*(5), 858–868.

Clark, A., D'Ambrosio, C., & Ghislandi, S. (2013). Poverty and Well-Being: Panel Evidence from Germany. *Paris School of Economics - Working Paper*(2007).

Collins, P. Y., Patel, V., Joestl, S., March, D., Insel, T. R., & Daar, A. S. (2011). Grand challenges in global mental health. *Nature*, *475*(N.A), 37–30.

De Quidt, J., & Haushofer, J. (2016). Depression for Economists. *NBER Working Paper*, 1–33.

Fasani, F., Farre, L., & Mueller, H. (2015). Feeling Useless : The Effect of Unemployment on Mental Health in the Great Recession. *IZA Discussion Paper*.

Friedrich, M. (2017). Depression Is the Leading Cause of Disability Around the World. *Journal of the American Medical Association*, *317*(15), 1517. doi: 10.1001/jama.2017.3826

Frijters, P., Haisken-DeNew, J. P., & Shields, M. A. (2004). Money Does Matter ! Evidence from Increasing Real Income and Life Satisfaction in East Germany Following Reunification. *The American Economic Review*, *94*(3), 730–740.

Frijters, P., Haisken-DeNew, J. P., & Shields, M. A. (2005). The causal effect of income on health: Evidence from German reunification. *Journal of Health Economics*, *24*(5), 997–1017.

Frijters, P., Johnston, D. W., & Shields, M. A. (2014). The Effect of Mental Health on Employment: Evidence from Australian Panel Data. *Health economics*, *23*, 1058–1071.

Gardner, J., & Oswald, A. J. (2007). Money and mental wellbeing: A longitudinal study of medium-sized lottery wins. *Journal of Health Economics*, *26*(1), 49–60.

González, P., Nuñez, A., Merz, E., Brintz, C., Weitzman, O., Navas, E. L., ... Gallo, L. C. (2017). Measurement properties of the Center for Epidemiologic Studies Depression Scale (CES-D 10): Findings from HCHS/SOL. *Psychological Assessment*, *29*(4), 372–381.

Graham, C., & Pettinato, S. (2002). Frustrated Achievers: Winners, Losers and Subjective Well-Being in New Market Economies. *The Journal of Development Studies*, *38*(4), 100–140.

Guvenen, F. (2007). Learning your earning: Are labor income shocks really very persistent? *American Economic Review*, *97*(3), 687–712.

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. *Journal of epidemiology and community health*, *62*(6), 538–544.

Harvey, P. O., Le Bastard, G., Pochon, J. B., Levy, R., Allilaire, J. F., Dubois, B., & Fossati, P. (2004). Executive functions and updating of the contents of working memory in unipolar depression. *Journal of Psychiatric Research*, *38*(6), 567–576.

Haushofer, J., & Fehr, E. (2014, may). On the psychology of poverty. *Science*, *344*(6186), 862–7.

Haushofer, J., & Shapiro, J. (2016). The short-term impact of unconditional cash transfers to the poor: Experimental evidence from kenya. *Quarterly Journal of Economics*, *131*(4), 1973–2042. doi: 10.1093/qje/qjw025

Hays, R. D., Wells, K. B., Sherbourne, C. D., Rogers, W., & Spritzer, K. (1995). Functioning and well-being outcomes of patients with depression compared with chronic general medical illnesses. *Archives of General Psychiatry*, *52*(1), 11–9.

Hubbard, N. A., Hutchison, J. L., Turner, M., Montroy, J., Bowles, R. P., & Rypma, B. (2016). Depressive thoughts limit working memory capacity in dysphoria. *Cognition and Emotion*, *30*(2), 193–209.

Hugo, C. J., Boshoff, D. E. L., Traut, A., Zungu-Dirwayi, N., & Stein, D. J. (2003). Community attitudes toward and knowledge of mental illness in South Africa. *Social Psychiatry and Psychiatric Epidemiology*, *38*(12), 715–719.

Johnes, G., & Johnes, J. (2004). International Handbook on the Economics of Education. *Knowledge Creation Diffusion Utilization*, *28*(6), 1578–1580.

Kahneman, D., & Deaton, A. (2010). High income improves evaluation of life but not emotional well-being. *Proceedings of the National Academy of Sciences*, *107*(38), 16489–93. doi: 10.1073/pnas.1011492107

Leibbrandt, M., Finn, A., & Woolard, I. (2012). Describing and decomposing post-apartheid income inequality in South Africa. *Development Southern Africa*, *29*(1), 19–34.

Lund, C., De Silva, M., Plagerson, S., Cooper, S., Chisholm, D., Das, J., ... Patel, V. (2011). Poverty and mental disorders: Breaking the cycle in low-income and middle-income countries. *The Lancet*, *378*(9801), 1502–1514.

Lybbert, T. J., Barrett, C. B., Desta, S., & Coppock, D. L. (2004, oct). Stochastic wealth dynamics and risk management among a poor population. *The Economic Journal*, *114*(498), 750–777.

Lybbert, T. J., & Wydick, B. (2018). Poverty, Aspirations, and the Economics of Hope. *Economic Development and Cultural Change*.

Macours, K., Schady, N., & Vakis, R. (2012, apr). Cash Transfers, Behavioral Changes, and Cognitive Development in Early Childhood: Evidence from a Randomized Experiment. *American Economic Journal: Applied Economics*, *4*(2), 247–273. doi: 10.1257/app.4.2.247

Magnac, T. (2000). Subsidised Training and Youth Employment : Distinguishing Unobserved Heterogeneity from State Dependence in Labour Market Histories. *The Economic Journal*, *110*(466), 805–837.

Mani, A., Mullainathan, S., Shafir, E., & Zhao, J. (2013, aug). Poverty impedes cognitive function. *Science*, *341*(6149), 976–80.

Marcus, J. (2013). The effect of unemployment on the mental health of spouses - Evidence from plant closures in Germany. *Journal of Health Economics*, *32*(3), 546–558.

McInerney, M., Mellor, J. M., & Nicholas, L. H. (2013). Recession depression: Mental health effects of the 2008 stock market crash. *Journal of Health Economics*, *32*(6), 1090–1104.

McKenzie, D. J., & Woodruff, C. (2006). Do Entry Costs Provide an Empirical Basis for Poverty Traps? Evidence from Mexican Microenterprises. *Economic Development and Cultural Change*, *55*(1), 3–42.

Meghir, C., & Pistaferri, L. (2004). Income Variance Dynamics and Heterogeneity. *Econometrica*, *72*(1), 1–32.

Murphy, F. C., Rubinsztein, J. S., Michael, A., Rogers, R. D., Robbins, T. W., Paykel, E. S., & Sahakian, B. J. (2001). Decision-making cognition in mania and depression. *Psychological medicine*, *31*(4), 679–693.

Myer, L., Smit, J., Roux, L. L., Parker, S., Stein, D. J., & Seedat, S. (2008). Common mental disorders among HIV-infected individuals in South Africa: prevalence, predictors, and validation of brief psychiatric rating scales. *AIDS patient care and STDs*, *22*(2), 147–158.

Ormel, J., Oldehinkel, T., Brilman, E., & Brink, W. v. (1993). Outcome of Depression and Anxiety in Primary Care. *Archives of General Psychiatry*, *50*(10), 759.

Ormel, J., VonKorff, M., Ustun, B., Pini, S., Korten, A., & Oldehinkel, T. (1994). Common Mental Disorders and Disability Across Cultures: Results from the WHO Collaborative

Study on Psychological Problems in General Health Care. *Journal of the American Medical Association*, *272*(22), 1741–1748.

Ozer, E. J., Fernald, L. C. H., Weber, A., Flynn, E. P., & VanderWeele, T. J. (2011). Does alleviating poverty affect mothers' depressive symptoms? A quasi-experimental investigation of Mexico's Oportunidades programme. *International Journal of Epidemiology*, *40*(6), 1565–1576.

Peng, L., Meyerhoefer, C. D., & Zuvekas, S. H. (2015). The Short-Term Effect of Depressive Symptoms on Labor Market Outcomes. *Health Economics*, *19*(11).

Radloff, L. S. (1977). The CES-D Scale: A Self-Report Depression Scale for Research in the General Population. *Applied Psychological Measurement*, *1*(3), 385–401.

Ran, M. S., Xiang, M. Z., Chan, C. L. W., Leff, J., Simpson, P., Huang, M. S., ... Li, S. G. (2003). Effectiveness of psychoeducational intervention for rural Chinese families experiencing schizophrenia - A randomised controlled trial. *Social Psychiatry and Psychiatric Epidemiology*, *38*(2), 69–75.

Samuels, F., & Stavropoulou, M. (2016). Being Able to Breathe Again': The Effects of Cash Transfer Programmes on Psychosocial Wellbeing. *The Journal of Development Studies*, *52*(8), 1099–1114.

Santor, D. A., Gregus, M., & Welch, A. (2006). Eight Decades of Measurement in Depression. *Measurement: Interdisciplinary Research & Perspective*, *4*(3), 135–155.

Saylor, C. F., Edwards, G. L., & McIntosh, J. A. (1987). Children's Depression Inventory: Reliability over repeated administrations. *Journal of Clinical Child ...*, *16*(4), 339–341.

Schilbach, F. (2015). Alcohol and Self-Control: A Field Experiment in India. *Working Paper*.

Schilbach, F., Schofield, H., & Mullainathan, S. (2016). The psychological lives of the poor. *American Economic Review Paper & Proceedings*, *106*(5), 435–440.

Sen, A. (1999). Development as Freedom. *Oxford Press*, 1–50.

Siddaway, A. P., Wood, A. M., & Taylor, P. J. (2017). The Center for Epidemiologic Studies-Depression (CES-D) scale measures a continuum from well-being to depression: Testing two key predictions of positive clinical psychology. *Journal of Affective Disorders*, *213*, 180–186.

Smoski, M. J., Lynch, T. R., Rosenthal, M. Z., Cheavens, J. S., Chapman, A. L., & Krishnan, R. R. (2008). Decision-making and risk aversion among depressive adults. *Journal of Behavior Therapy and Experimental Psychiatry*, *39*(4), 567–576.

Snyder, H. R. (2013). Major depressive disorder is associated with broad impairments on neuropsychological measures of executive function: a meta-analysis and review. *Psychological bulletin*, *139*(1), 81–132.

Spijker, J., Graaf, R., Bijl, R. V., Beekman, a. T. F., Ormel, J., & Nolen, W. a. (2004). Functional disability and depression in the general population. Results from the Netherlands Mental Health Survey and Incidence Study (NEMESIS). *Acta psychiatrica Scandinavica*, *110*(3), 208–14.

Stevenson, B., & Wolfers, J. (2013). Subjective Well-Being and Income: Is There Any Evidence of Satiation? *American Economic Review: Papers & Proceedings*, *103*(1033), 598–604. doi: 10.1257/aer.103.3.598

Winkelmann, L., & Winkelmann, R. (1998). Why are the Unemployed So Unhappy ?

Evidence from Panel Data. *Economica*, *65*(257), 1–15.
Wood, A. M., Taylor, P. J., & Joseph, S. (2010). Does the CES-D measure a continuum from depression to happiness? Comparing substantive and artifactual models. *Psychiatry Research*, *177*(1-2), 120–123.
Woolard, I., Buthelezi, T., & Bertscher, J. (2012). Child Grants: Analysis of the NIDS Wave 1 and 2 Datasets. *NIDS Discussion Paper*, *7*(84).
World Heath Organization. (2017). *Depression and Other Common Mental Disorders: Global Health Estimates* (Tech. Rep.). Geneva: World Health Organization.
Yechiam, E., Busemeyer, J. R., & Stout, J. C. (2004). Using Cognitive Models to Map Relations between Neuropsychological Disorders and Human Decision Making Deficits. *Psychological Science*, *16*(12), 973–978.
Zhang, W., O'Brien, N., Forrest, J. I., Salters, K. A., Patterson, T. L., Montaner, J. S. G., ... Lima, V. D. (2012). Validating a shortened depression scale (10 item CES-D) among HIV-Positive people in British Columbia, Canada. *PLoS ONE*, *7*(7), 1–5.

Tables

Table 1: Whole Sample vs Sample used in paper (NIDS)

	Wave 4 NIDS	Main Study Sample
VARIABLES - Wave 4	Mean	Mean
Household Income Per Capita (ZAR)	2,568	2,302
Household Food Expenditure Per Capita (ZAR)	408	379
Individual Income (ZAR)	2,888	2,574
CES-D score	7.17	7.17
Household Size	4.7	4.83
Female	0.55	0.6
Age	41.9	43.7
Observations	11,687	6,975

Notes: Wave 4 NIDS sample excludes anyone under the age of 21 to be comparable to the study sample. The sample in this study include individuals who completed the individual section of the survey including the CES-D section for all four rounds of NIDS. The two are comparable, however the sample used in this study appears to be slightly poorer and a larger fraction is female.

Table 2: System GMM Estimates

	Assumptions A	Assumptions B
	(1)	(2)
Dependent Variable: Individual Income		
$CES\text{-}D_t$	-39.61	-212.58
	(92.04)	(161.92)
$individualincome_{t\text{-}1}$	0.669***	0.472***
	(0.183)	(0.166)
Dependent Variable: CES-D		
$hhincome\_percapita_t$	-.00356***	-.00470***
	(0.00085)	(0.00096)
$hhincome\_percapita^2{}_t$	0.00000024***	0.00000034***
	(0.000)	(0.000)
$CES\text{-}D_{t\text{-}1}$	0.411***	0.291
	(0.148)	(0.493)
Controls	Yes	Yes
Observations	6,974	6,974

Cluster robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Notes: Controls include household size and marital status. Two-stage GMM for the whole sample under the two assumptions (A and B) show similar statistically significant results for the impact of income on CES-D but different statistically insignificant point estimates for the impact of CES-D on income.

Table 3: Impact of CES-D and Depression on Individual Income

	Assumptions A		Assumptions B	
	Individual Income		**Individual Income**	
	(1)	(2)	(3)	(4)
CES-D$_t$	-386.33***	-211.70*	-1,231.44**	-317.53**
	(126.56)	(111.92)	(554.83)	(153.20)
individualincome$_{t-1}$		0.288**		0.1547
		(0.140)		(0.113)
Controls	Yes	Yes		Yes
Observations	5,499	5,499	5,499	5,499

Cluster robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Notes: Controls include household size and marital status. Using two different instrument matrices, I find similar results on the average effect of CES-D on individual income (Column 2 and 4) when restricting the sample to working age adults. The results here illustrate that excluding the lagged dependent variable significantly alters the results. It is worth noting that for working age adults, the coefficients on the other equation in the system are similar to those for the whole sample in Table 2.

Table 4: Impact of CES-D on Individual Income - Thresholds

	Individual Income					
	(1)	(2)	(3)	(4)	(5)	(6)
CES-D Threshold =	***7***	***8***	***9***	***10***	***11***	***12***
CES-D$_t$	-136.227	-182.203	-245.625	-394.765**	-496.814***	-422.051***
	(161.88)	(169.38)	(157.51)	(158.09)	(144.94)	(129.62)
Lagged Dependent	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,905	3,366	2,885	2,378	1,917	1,517

Cluster robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Notes: Controls include household size and marital status. It is clear that those who experience the threshold of 10 show statistically significant negative effects of CES-D on income. This suggest nonlinearities in the effect of CES-D on individual income. Results are based on the instruments requiring assumptions A. The results from the less restrictive assumptions B are similar and exhibit a similar pattern around the threshold.

Table 5: Mechanisms and Other Effects

	Labor Force Participation (1)	**Employed (Given in Labor Force)** (2)	**Hours Worked Among Employed** (3)	**Temptation Good Exp Share** (4)	**Social Cohesion** (5)	**Hopeful about the Future** (6)
CES-D$_t$	-.071**	-0.098*	-5.76*	0.0060*	-.129**	-0.138*
	(0.03)	(0.06)	(3.34)	(0.00)	(0.06)	(0.08)
Lagged Dependent	Yes	No	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5,187	2,800	2,487	5,387	2,611	3,885

Cluster robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Notes: Controls include household size, marital status, household per capita income, and household per capita food expenditure (both instrumented with lagged levels as above). Moment conditions requiring adapted assumptions similar to set of assumptions A are used to estimate these results.

Table 6: Full Sample shows larger point estimates of Expenditure/Income on CES-D

	Assumptions A			Assumptions B			Alternative Instrument
	CES-D			**CES-D**			**CES-D**
	(1)	(2)*	(3)*	(4)	(5)*	(6)*	(7)
$hhincome\_percapita_t$	-0.00356***			-0.00470***			-0.0041**
	(0.0009)			(0.001)			(0.002)
$hhincome\_percapita^2{}_t$	0.00000024***			0.00000034***			0.00
	(0.000000074)			(0.0000001)			(0.00)
$foodexp\_percapita_t$		-0.00801**			-0.0101**		
		(0.00317)			(0.004)		
$foodexp\_percapita^2{}_t$		0.00			0.00		
		(0.00)			(0.00)		
$wealthindex_t$			-3.179**			-3.327**	
			(1.23)			(1.46)	
$CES\text{-}D_{t-1}$	0.411***	-0.281	0.0546	0.291	0.0824	0.053	0.033
	(0.148)	(0.43)	(0.04)	(0.493)	(0.50)	(0.04)	(0.05)
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,975	6,099	6,975	6,975	6,103	6,975	34,961

Cluster robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Controls include household size, marital status, household per capita income, and household per capita food expenditure.
*Single equation GMM used to estimate coefficients.

Table 7: Dynamic Specification shows larger effects of Expenditure/Income on CES-D for Poorer Sample

	Poorest 54%		Poorest 20%	
	CES-D		**CES-D**	
	(1)	(2)*	(3)	(4)*
hhincome_percapita$_t$	-0.00445***		-0.0051***	
	(0.00)		(0.00)	
hhincome_percapita$^2{}_t$	0.00000056**		0.00000048*	
	(0.00000026)		(0.00000026)	
foodexp_percapita$_t$		-0.024**		-0.027**
		(0.012)		(0.013)
foodexp_percapita$^2{}_t$		.00002**		0.00001
		(0.0000096)		(0.00001)
CES-D$_{t\text{-}1}$	0.548	0.138***	0.373	0.126*
	(0.492)	(0.049)	(0.263)	(0.065)
Controls	Yes	Yes	Yes	Yes
Observations	3,776	3,705	1,459	1,456

Cluster robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Controls include household size and marital status. Poverty level is determined by the wealth index in wave 3.
Instruments requiring set of assumptions A used to estimate the models.
54% is the poverty head count according South Africa Labor and Development Research Unit research paper
*Single equation GMM used to estimate coefficients.

Table 8: Log Transformations Yield Similar Results

	Full Sample		Poorest 54%		Poorest 20%	
	CES-D		**CES-D**		**CES-D**	
	(1)	(2)	(3)	(4)	(5)	(6)
Log(hhincome_percapita$_t$)	-2.06**		-2.55***		-4.44***	
	(0.833)		(0.668)		(1.429)	
Log(foodexp_percapita$_t$)		-2.390		-3.060**		-4.705**
		(1.71)		(1.54)		(2.11)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	6,968	6,100	3,633	3,274	1,374	1,374

Cluster robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Controls include lagged dependent, household size, and marital status. Poverty level is determined by the wealth index in wave 3.
Instruments requiring Assumptions A used. Less restrictive Assumptions B produce similar results.
Using Log transformations allows for the easier percentage interpretation.

Figures

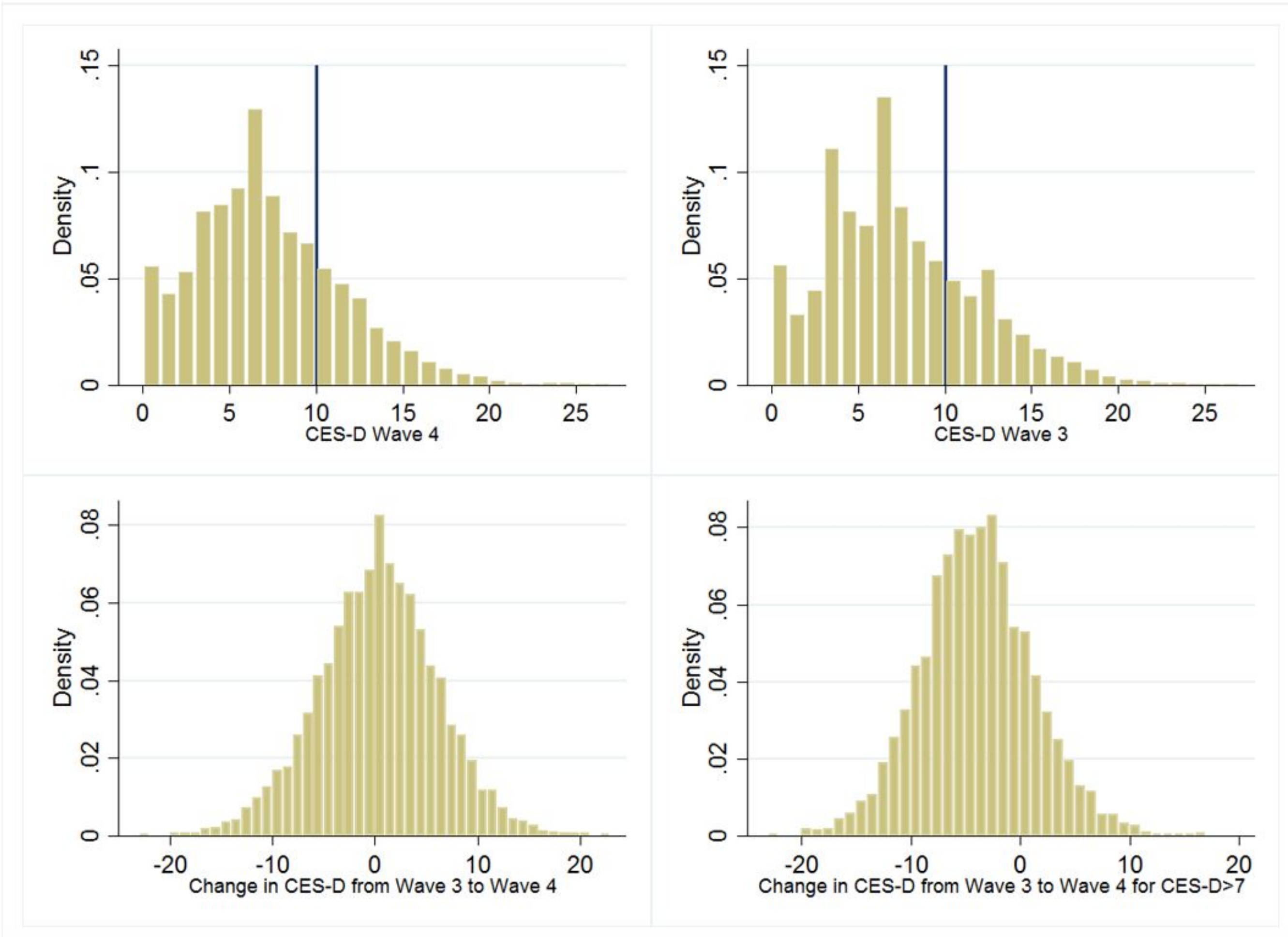

Figure 1: Histograms of the CES-D scores in wave four and wave three show that a significant portion of the population are above the threshold of 10 used by psychologists to screen for depression. The two lower histograms compare changes between wave three and wave four for the whole sample and specifically for individuals with CES-D scores in wave three of 8 and above. A significant portion of those with scores of 8 or above exhibit a positive change which indicates worsening depressive symptoms.

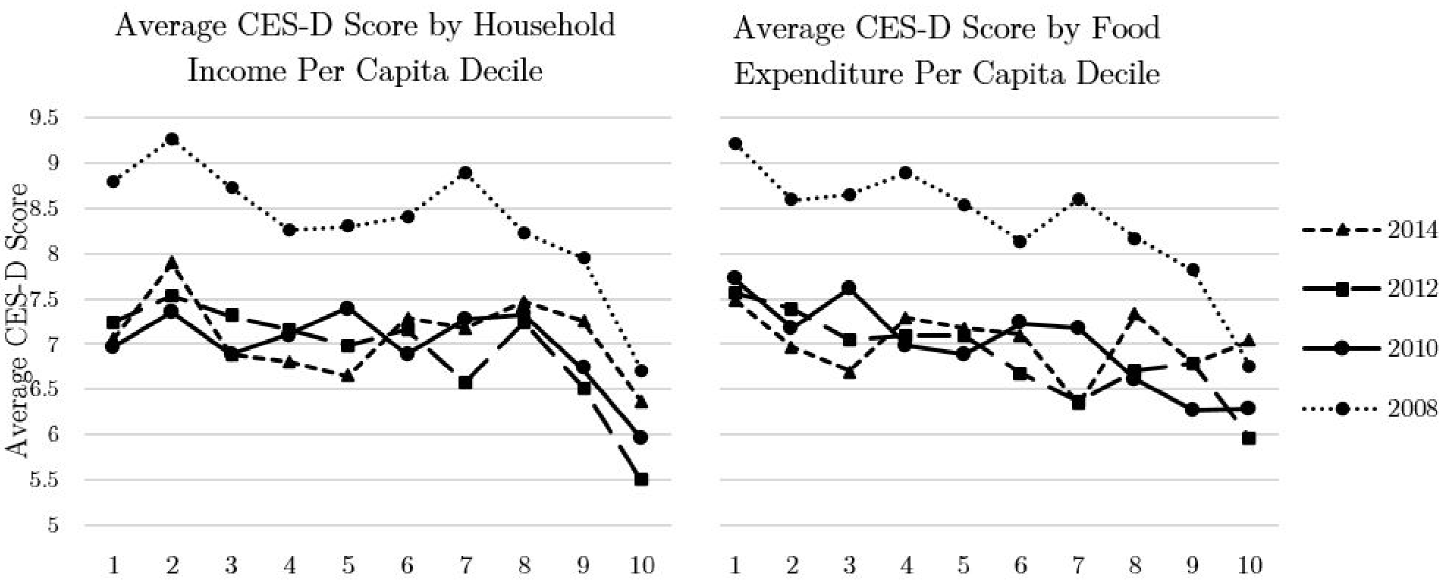

Figure 2: Average CES-D scores decrease with income and expenditure deciles indicating that psychological well-being is correlated with economic well-being. Standard deviations within each decile range from 3.8 to 4.8 and do not exhibit a pattern.

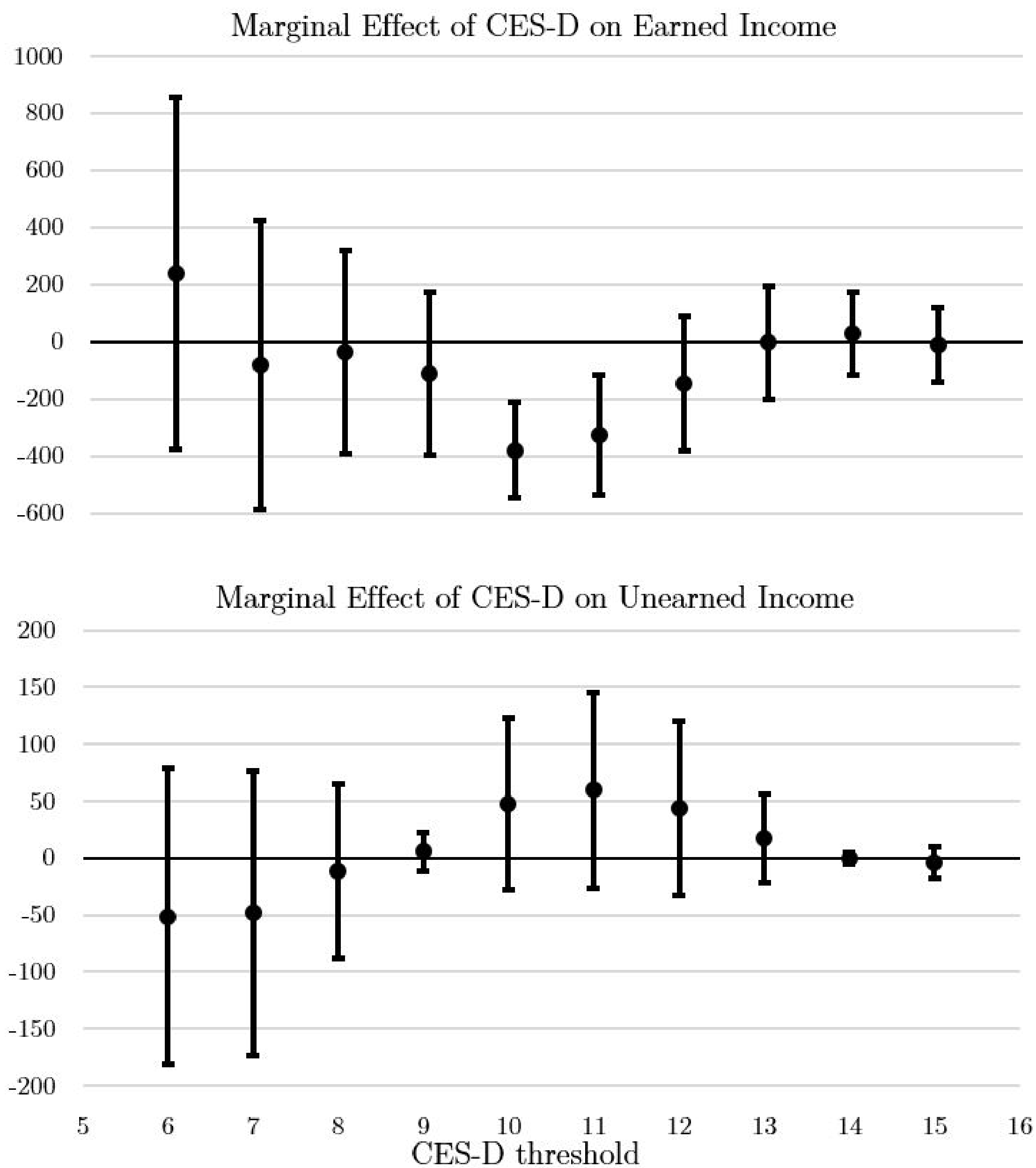

Figure 3: Impact of CES-D on earned (upper) and unearned (lower) income based on CES-D score threshold show that, as hypothesized, changes in CES-D that include or are above the thresholds only affect earned income.

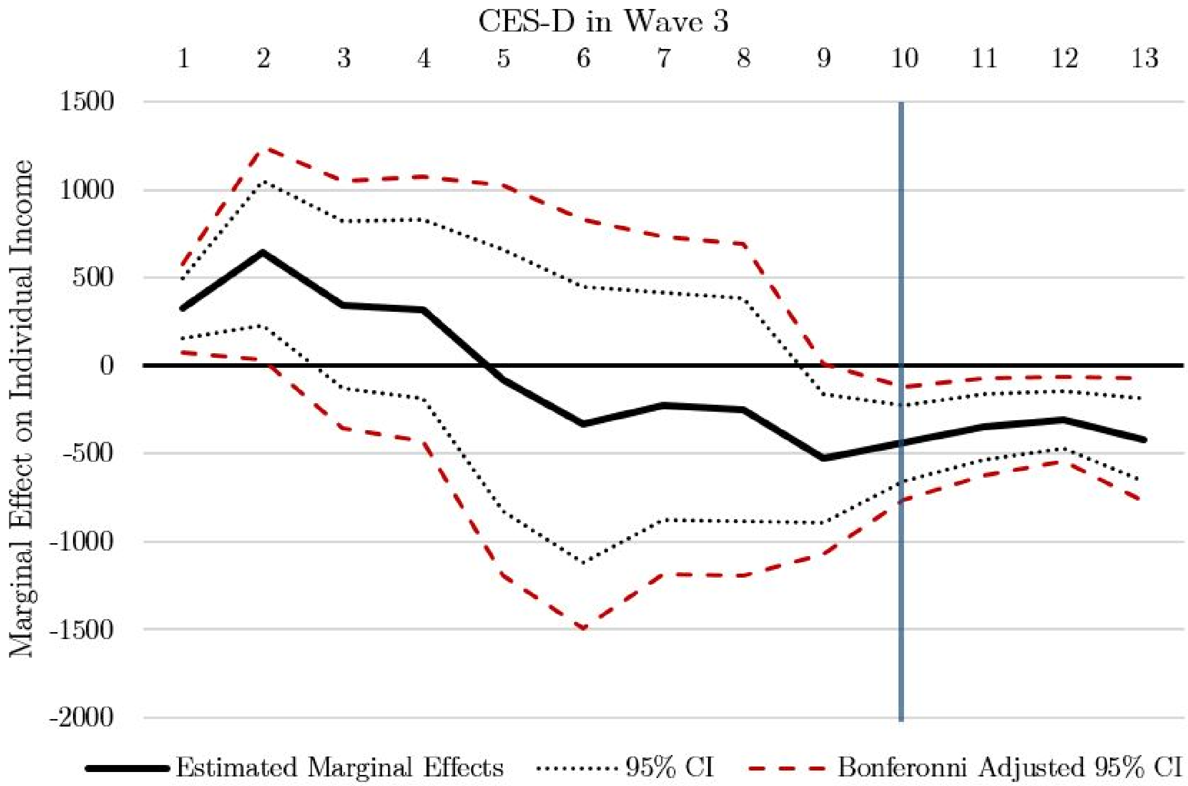

Figure 4: Impact of CES-D on Individual Income based on CES-D score in Wave 3. This figure was based on 13 local linear regressions with a bandwidth of 1 and restricted to individuals who experienced changes with absolute value less than or equal to the 4 on the CES-D scale. Red dashed confidence intervals correct for multiple testing. The blue vertical line at 10 indicates the threshold used by psychologists to screen for depression. The point estimates are presented in Appendix C Table A6. This figure was estimated with $Z^A_{i,t}$, however, estimating the figure with matrix $Z^B_{i,t}$ showed very a very similar pattern and point estimates.

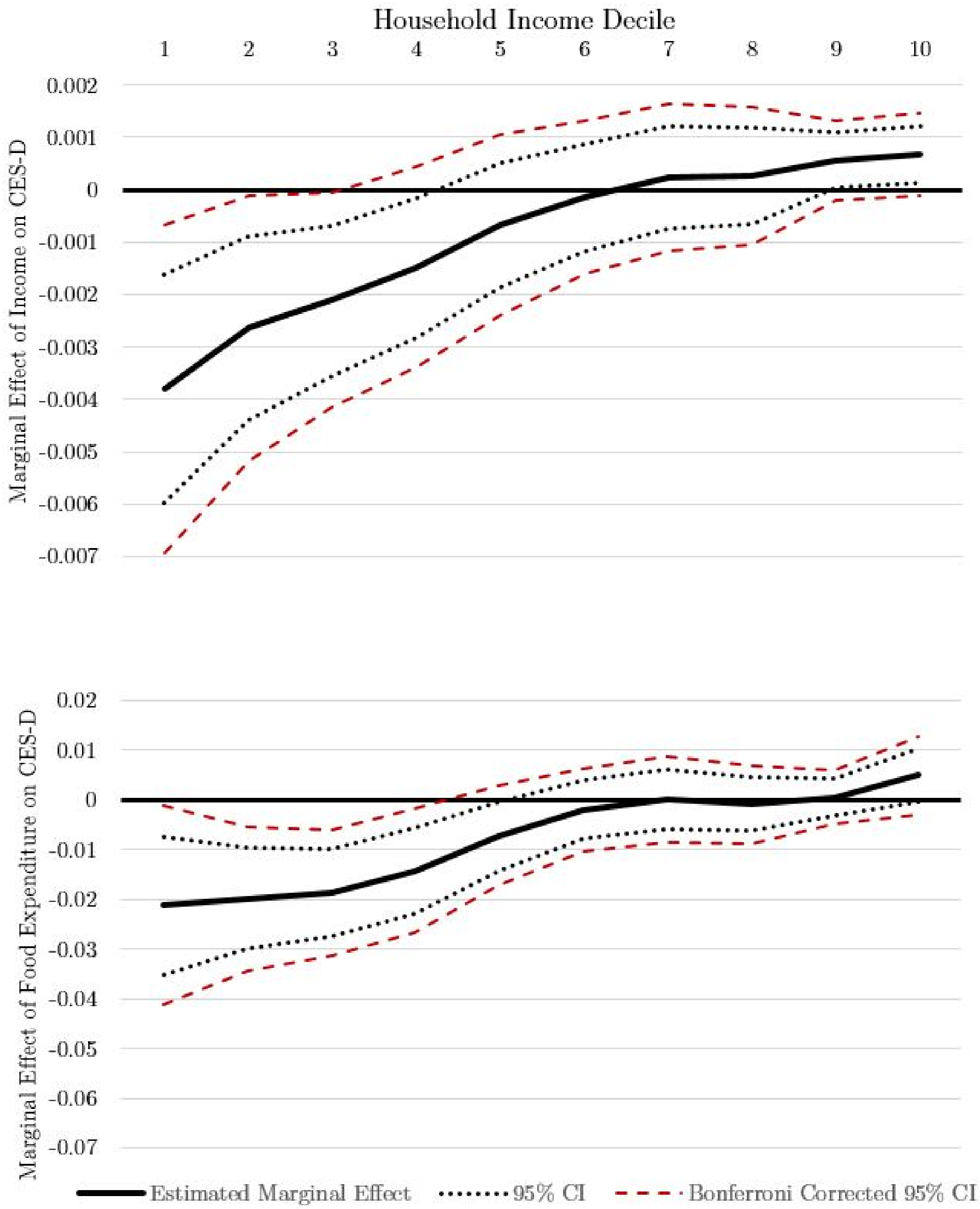

Figure 5: The figures above show the marginal effect of changes in income (ZAR) (upper) and food expenditure per capita changes (lower). The marginal effect of changes in household income per capita on CES-D are evident only for those in the lower income deciles. Despite much smaller sample sizes for each regression, the effect of income on CES-D is statistically significant for the lowest three (and four for food expenditure) deciles even after a conservative Bonferroni CI correction for multiple testing. The impact of changes in income and food expenditure per capita on psychological well-being is not statistically different from zero for the upper deciles.

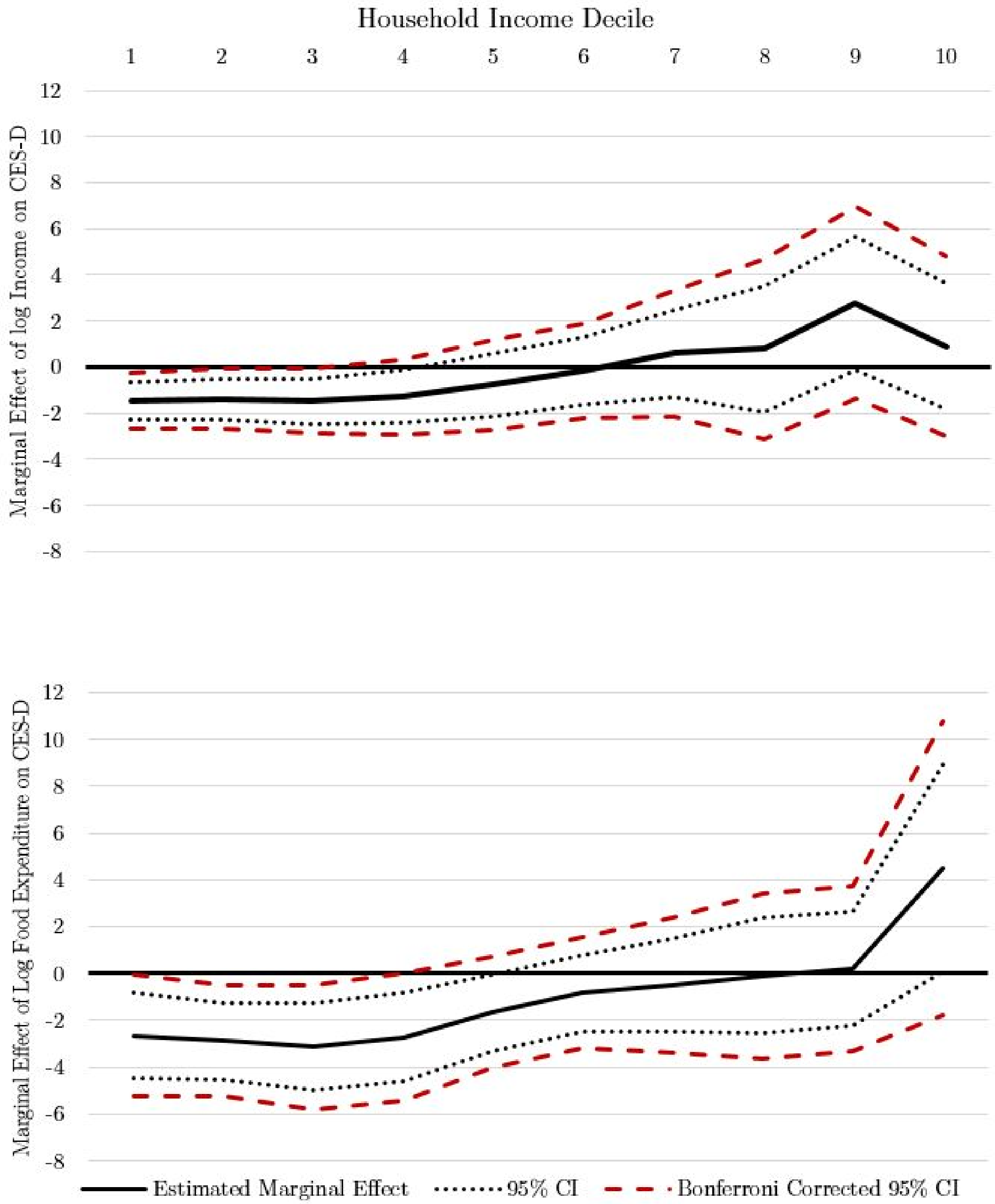

Figure 6: The same pattern as in Figure 6 emerges when considering percent changes in income, however, the statistically significant estimates for the lowest 4 household income deciles are relatively similar in magnitude.

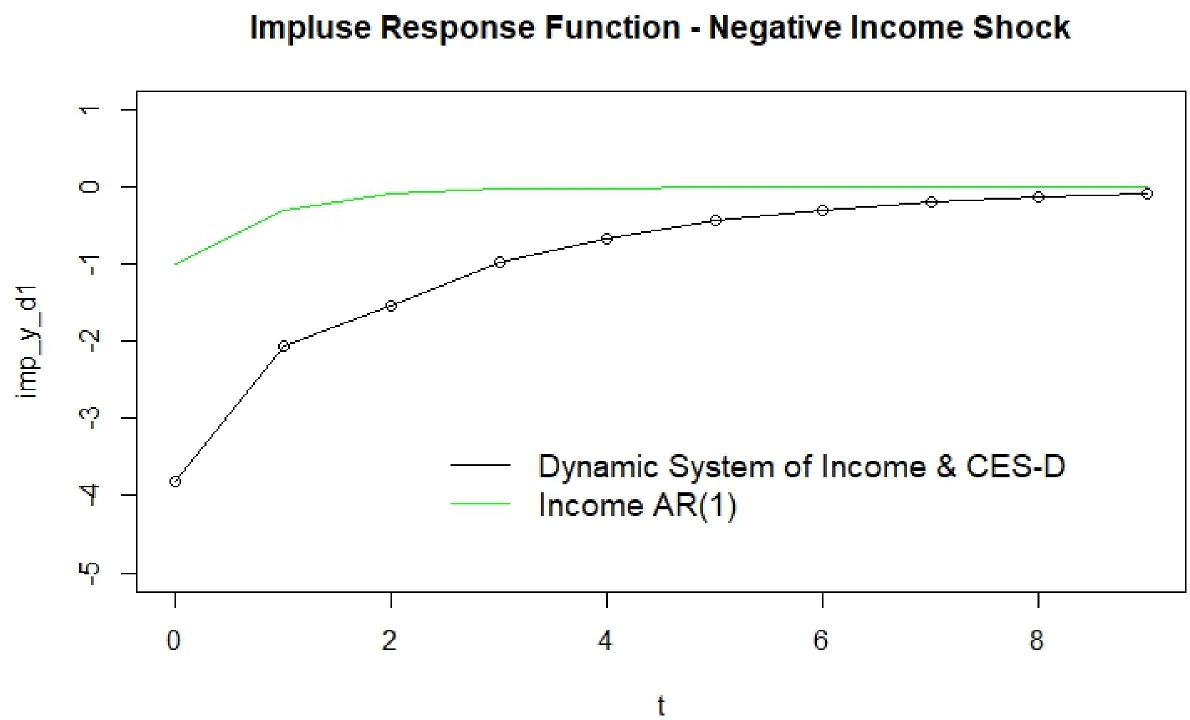

Figure 7: Impulse response function: the effect of a shock to income in time 0 on future income for a household with one individual.

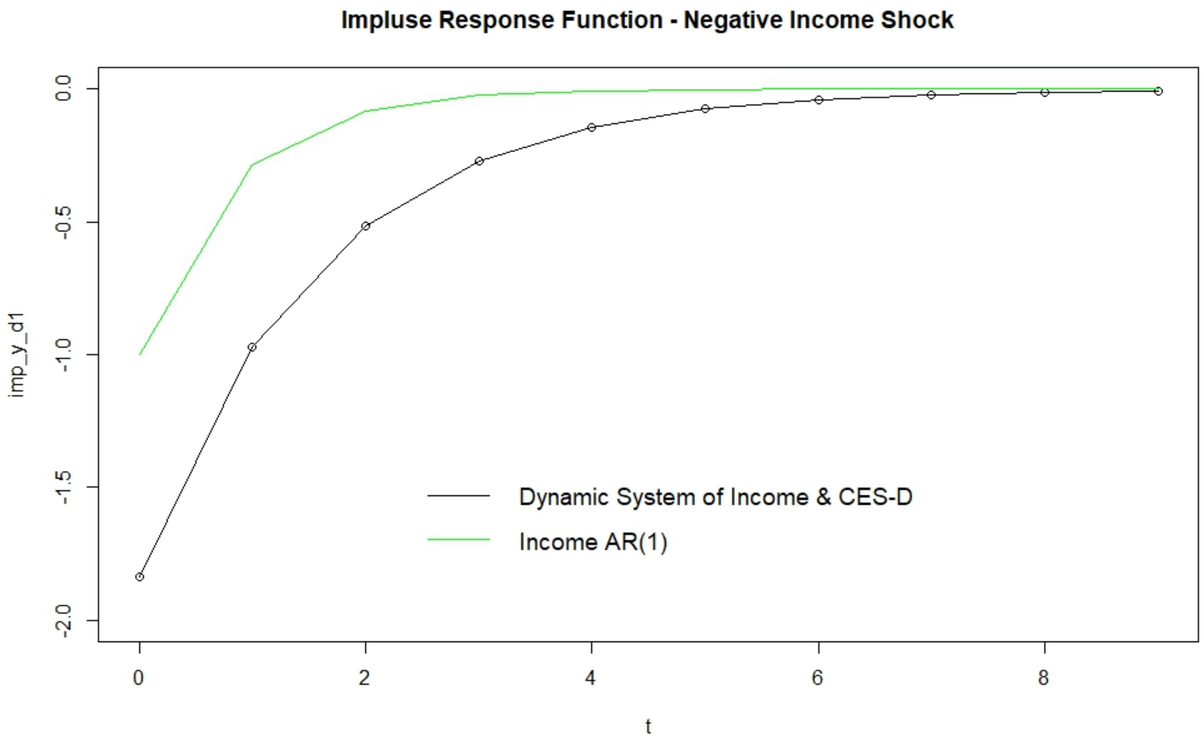

Figure 8: Impulse response function: the effect of a shock to income in time 0 on future income.

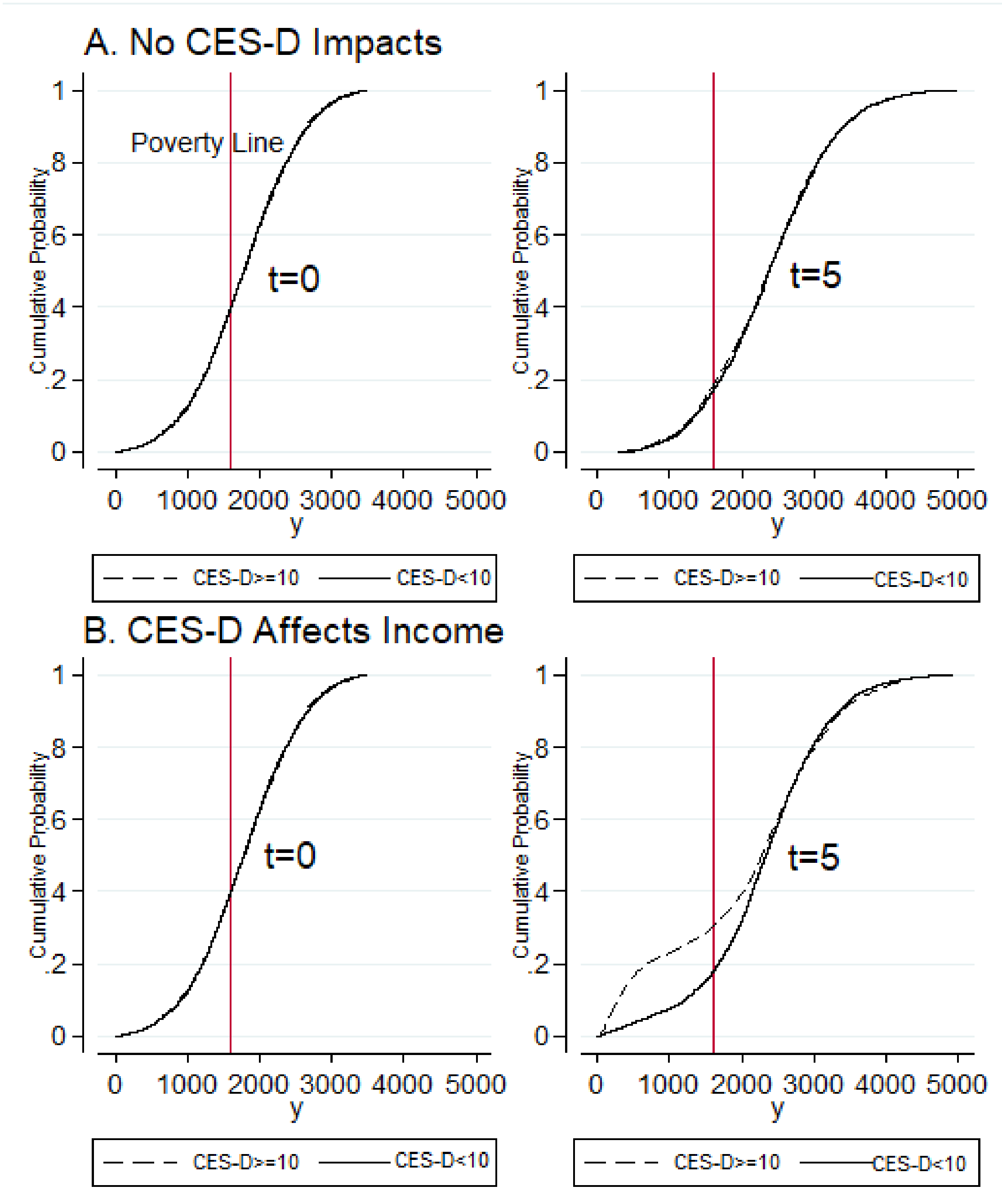

Figure 9: Top (A) shows income at time 0 and after 5 periods; if CES-D plays no role then initial levels of CES-D will not affect the distribution of income over time. In the lower part of the Figure (B), the full system of equations estimated above shows that when psychological well-being plays a role, those who randomly begin with lower levels of psychological well-being will have higher rates of poverty in the future.

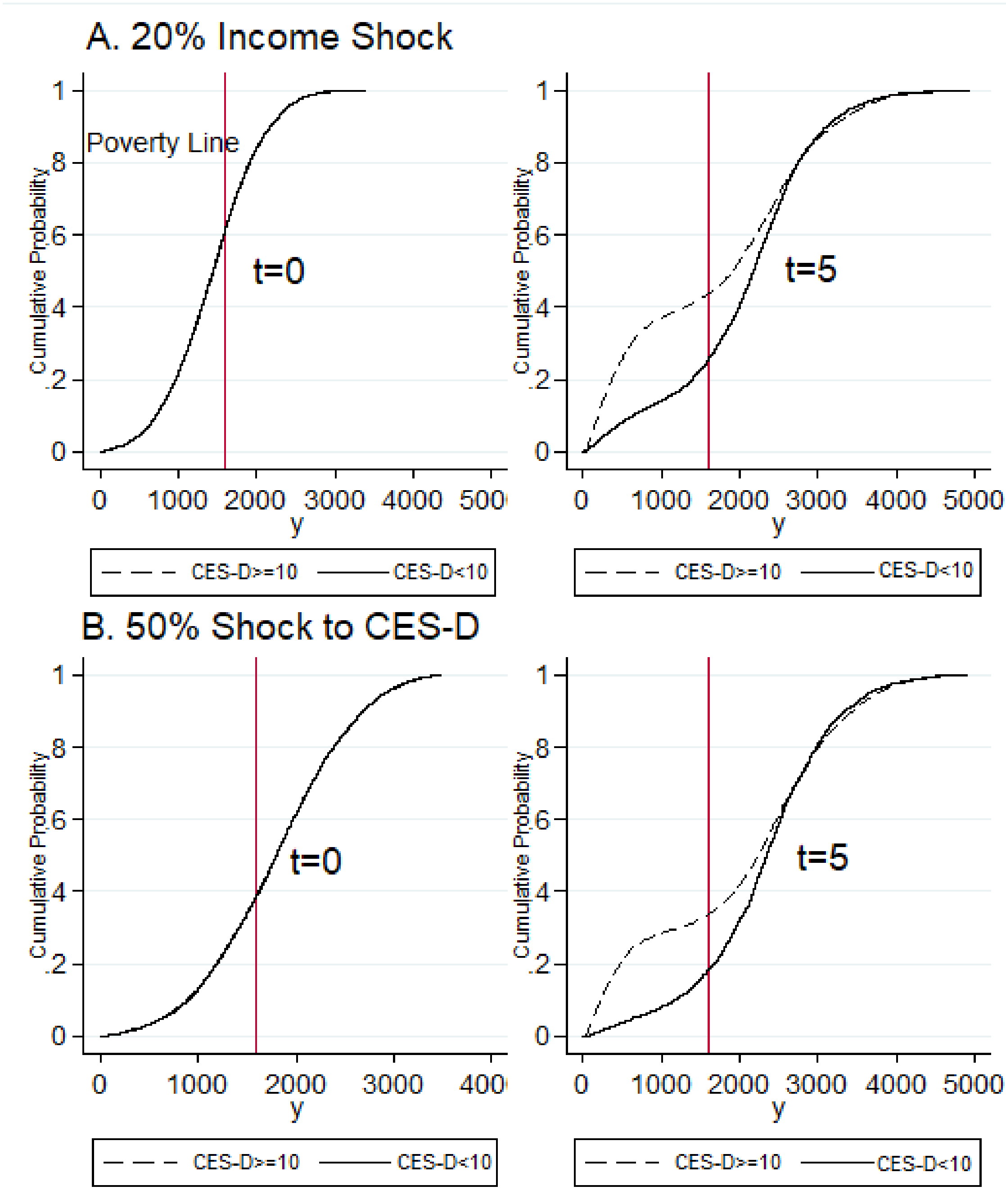

Figure 10: The effect of psychological well-being on poverty rates over time is accentuated after negative shocks to either income or psychological well-being. The difference in the poverty rate in the two groups after an across-the-board negative shock to either income or psychological well-being is larger than those in Figure 9.B.

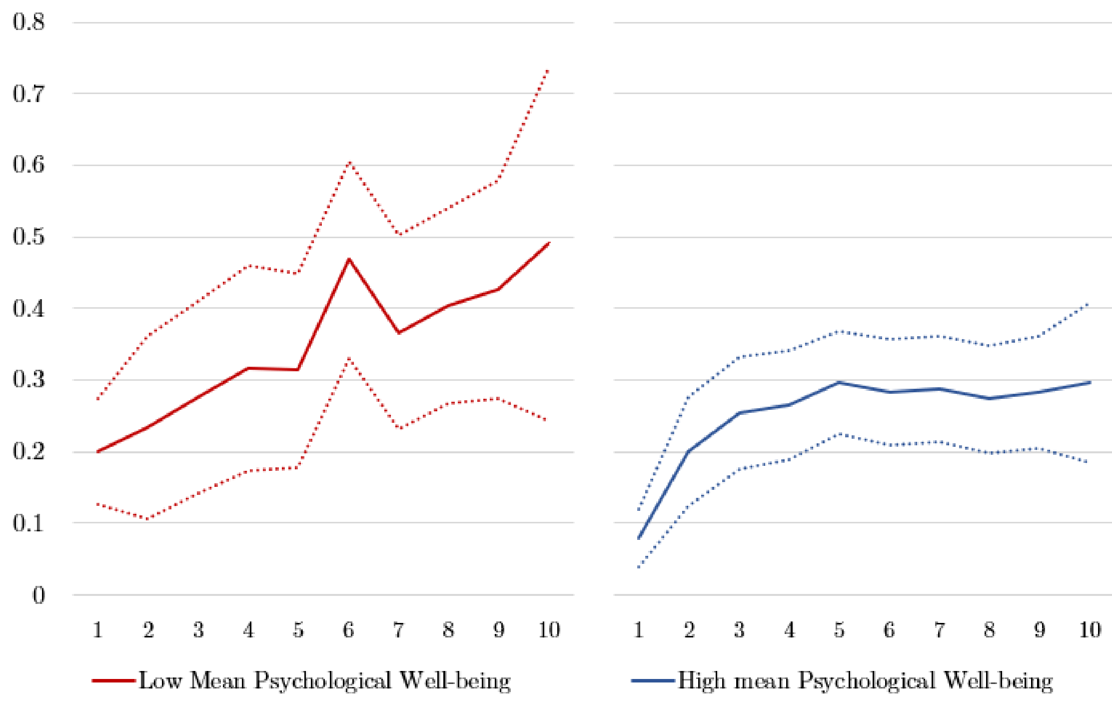

Figure 11: Probability of experiencing negative income growth (between Wave 3 and 4) by household income per capita decile for two subsamples: Households with a head that experiences low psychological well-being in Wave 1 and 2 and all other households.

Appendix

A. Proofs

The **proposition** states that under assumptions A, instruments matrix $Z^A_{i,t}$ would imply moment conditions to consistently estimate the coefficients of the following system of equations (3) and (4) in Section 4. The moment conditions are:

$$E\left(Z^{A\prime}_{i,t} U_{i,t}\right) = \mathbf{0}$$

where $U_{i,t}$ is a vector of the first-differenced unobserved error terms $\Delta e_{i,t}$ and $\Delta u_{i,t}$. I expand the left hand side of the equation below:

$$E\left[\begin{pmatrix} z^{1}_{i,t}{}' & \mathbf{0} \\ \mathbf{0} & z^{2}_{i,t}{}' \end{pmatrix}\begin{pmatrix} \Delta e_{i,t} \\ \Delta u_{i,t} \end{pmatrix}\right] = E\left[\begin{pmatrix} z^{1}_{i,t}{}'\Delta e_{i,t} \\ z^{2}_{i,t}{}'\Delta u_{i,t} \end{pmatrix}\right] = \begin{pmatrix} E[z^{1}_{i,t}{}'e_{i,t} - z^{1}_{i,t}{}'e_{i,t-1}] \\ E[z^{2}_{i,t}{}'u_{i,t} - z^{2}_{i,t}{}'u_{i,t-1}] \end{pmatrix}$$

Distributing further and applying the law of iterated expectations gives:

$$\begin{pmatrix} D_{i,t-2}E\left[e_{i,t} \mid D_{i,t-2}\right] - D_{i,t-2}E[e_{i,t-1}|D_{i,t-2}] \\ D_{i,t-3}E\left[e_{i,t} \mid D_{i,t-3}\right] - D_{i,t-3}E[e_{i,t-1}|D_{i,t-3}] \\ y_{i,t-3}E\left[e_{i,t} \mid y_{i,t-3}\right] - y_{i,t-3}E[e_{i,t-1}|y_{i,t-3}] \\ D_{i,t-3}E[u_{i,t}|D_{i,t-3}] - D_{i,t-3}E[u_{i,t-1}|D_{i,t-3}] \\ h_{i,t-2}E[u_{i,t}|h_{i,t-2}] - h_{i,t-2}E[u_{i,t-1}|h_{i,t-2}] \\ h_{i,t-3}E[u_{i,t}|h_{i,t-3}] - h_{i,t-3}E[u_{i,t-1}|h_{i,t-3}] \end{pmatrix}$$

Assumptions A

$$E\left[e_{i,t} \mid y_{i,t-2}, y_{i,t-3}, \ldots; D_{i,t-1}, D_{i,t-2}, \ldots; \boldsymbol{x}_{i,t}, \boldsymbol{x}_{i,t-1}, \ldots\right] = 0 \tag{A1}$$

and

$$E\left[u_{i,t} \mid h_{i,t-1}, h_{i,t-2}, \ldots; D_{i,t-2}, D_{i,t-3}, \ldots; \boldsymbol{x}_{i,t}, \boldsymbol{x}_{i,t-1}, \ldots\right] = 0 \tag{A2}$$

It is clear that under assumptions A, each term in the vector above would be equal to zero. Thus, assumptions A imply the moment conditions $E\left(Z^{A\prime}_{i,t} U_{i,t}\right) = \mathbf{0}$.[46]

The assumptions required for instruments matrix $Z^B_{i,t}$ to imply the moment conditions $E\left(Z^{B\prime}_{i,t} U_{i,t}\right) = \mathbf{0}$ are less restrictive and are the following:

$$E\left[e_{i,t} \mid y_{i,t-2}, y_{i,t-3}, \ldots; D_{i,t-2}, D_{i,t-3}, \ldots; \boldsymbol{x}_{i,t}, \boldsymbol{x}_{i,t-1}, \ldots\right] = 0 \tag{B1}$$

[46] There are six moment conditions and four coefficients and thus the coefficients are identified.

and

$$E\left[u_{i,t} \mid h_{i,t-2}, h_{i,t-3}, \ldots; D_{i,t-2}, D_{i,t-3}, \ldots; \boldsymbol{x}_{i,t}, \boldsymbol{x}_{i,t-1}, \ldots\right] = 0 \tag{B2}$$

Similarly, it is clear when expanding the left hand side that assumptions B imply the moment conditions:

$$\begin{pmatrix} D_{i,t-3}E\left[e_{i,t} \mid D_{i,t-3}\right] - D_{i,t-3}E[e_{i,t-1}|D_{i,t-3}] \\ y_{i,t-3}E\left[e_{i,t} \mid y_{i,t-3}\right] - y_{i,t-3}E[e_{i,t-1}|y_{i,t-3}] \\ D_{i,t-3}E[u_{i,t}|D_{i,t-3}] - D_{i,t-3}E[u_{i,t-1}|D_{i,t-3}] \\ h_{i,t-3}E[u_{i,t}|h_{i,t-3}] - h_{i,t-3}E[u_{i,t-1}|h_{i,t-3}] \end{pmatrix} = \mathbf{0}$$

Simulation results illustrating this estimation strategy and the assumptions required are presented in the next Appendix section B.

B. Simulations

I generate data from the following set of simultaneous equations:

$$y_{i,t} = -0.5x_{i,t} + 0.6y_{i,t-1} + e_{i,t}$$

$$x_{i,t} = -0.1y_{i,t} - 0.4x_{i,t-1} + u_{i,t}$$

where $y_{i,0}$ and $x_{i,0}$ are independently drawn from a $N(0,1)$ distribution. The error vector $U = \begin{pmatrix} e_{i,1} & e_{i,2} & e_{i,3} & e_{i,4} & u_{i,1} & u_{i,2} & u_{i,3} & u_{i,4} \end{pmatrix}$ are drawn from a $N(0,1)$ distribution with the following covariance matrices:

$$V = \begin{bmatrix} 1 & & & & & & & \\ \lambda_e & 1 & & & & & & \\ 0 & \lambda_e & 1 & & & & & \\ 0 & 0 & \lambda_e & 1 & & & & \\ \gamma & \zeta & 0 & 0 & 1 & & & \\ \zeta & \gamma & \zeta & 0 & \lambda_u & 1 & & \\ 0 & \zeta & \gamma & \zeta & 0 & \lambda_u & 1 & \\ 0 & 0 & \zeta & \gamma & 0 & 0 & \lambda_u & 1 \end{bmatrix}$$

where λ is the serial correlation between error terms, γ is the correlation between $e_{i,t}$ and $u_{i,t}$, and ζ is the correlation between $e_{i,t}$ and $u_{i,t-1}$.

To emulate my data, I then create $t = 4$ based on the equations above. I then estimate the following equations:

$$\Delta y_{i,t} = \alpha_1 \Delta x_{i,t} + \beta_1 \Delta y_{i,t-1} + \Delta e_{i,t}$$

$$\Delta x_{i,t} = a_1 \Delta y_{i,t} + b_2 \Delta x_{i,t-1} + \Delta u_{i,t}$$

using a two step GMM and two different instrument matrices $Z^A_{i,t}$ and $Z^B_{i,t}$ where

$$Z^A_{i,t} = \begin{pmatrix} x_{i,t-2} & x_{i,t-3} & y_{i,t-3} & 0 & 0 & 0 \\ 0 & 0 & 0 & x_{i,t-3} & y_{i,t-2} & y_{i,t-3} \end{pmatrix}$$

and

$$Z^B_{i,t} = \begin{pmatrix} x_{i,t-3} & y_{i,t-3} & 0 & 0 \\ 0 & 0 & x_{i,t-3} & y_{i,t-3} \end{pmatrix}$$

The results are presented in the tables below. Correlation between error terms in the same t (γ) do not affect the consistency of the results and in the simulations I assume that

$\gamma = -0.4$. It is clear that only in Table A1 does $Z_{i,t}^A$ provide consistent estimates. This is when λ and ζ are zero. Interestingly, if λ is different from zero but the model has no simultaneity (β_1 and α_1 are zero) then $Z_{i,t}^A$ will consistently estimate the coefficients of zero. These results are presented in the bottom half of table A1-3. If there is simultaneity, $Z_{i,t}^A$ will reject zero with high probability but the coefficients will be estimated with bias.

However the results in Table A4 show that if $\zeta \neq 0$ then $Z_{i,t}^A$ will not provide consistent estimates of coefficients equal to zero.

$Z_{i,t}^B$, however, consistently estimates all the coefficients for non-zero values of λ and ζ. However, serial correlation across more than 1 time period would create bias. This is not shown in the simulations but is obvious from both sets of Assumptions A and B.

Table A1: Simulation Results 1/4

		$Z_{i,t}^{A}$					$Z_{i,t}^{B}$				
$\lambda_e = 0, \lambda_u = 0, \gamma = 0.4, \zeta = 0$	**N**	**bias**	**ssd**	**sse/ssd**	**p5**	**p10**	**bias**	**ssd**	**sse/ssd**	**p5**	**p10**
					Main Equation						
$\beta_1 = -0.5$	200	0.003	0.285	0.886	0.573	0.667	-0.172	2.943	1.847	0.511	0.571
	500	0.002	0.167	0.960	0.851	0.902	0.005	0.461	0.798	0.609	0.670
	1000	-0.001	0.114	0.983	0.983	0.993	0.015	0.290	0.782	0.755	0.803
	5000	0.002	0.049	1.019	1.000	1.000	0.006	0.082	0.947	0.989	0.994
$\beta_2 = 0.6$	200	-0.019	0.261	0.931	0.714	0.818	-0.090	1.147	1.793	0.173	0.300
	500	-0.011	0.157	0.987	0.965	0.983	-0.004	0.462	0.783	0.636	0.769
	1000	-0.002	0.113	0.976	1.000	1.000	0.009	0.224	0.922	0.945	0.974
	5000	-0.002	0.049	0.992	1.000	1.000	0.003	0.078	0.994	1.000	1.000
$\alpha_1 = -0.1$	200	0.093	4.622	0.927	0.257	0.331	-1.710	52.881	1.499	0.245	0.298
	500	-0.007	0.255	0.874	0.189	0.272	0.040	0.884	0.747	0.163	0.213
	1000	0.006	0.177	0.887	0.192	0.278	0.017	0.482	0.652	0.145	0.200
	5000	0.000	0.072	0.959	0.366	0.460	0.003	0.123	0.983	0.195	0.261
$\alpha_2 = -0.4$	200	0.015	0.631	1.079	0.940	0.948	-0.317	8.785	1.536	0.411	0.513
	500	-0.001	0.053	0.992	0.997	0.998	-0.003	0.198	0.964	0.757	0.840
	1000	-0.001	0.037	1.003	1.000	1.000	0.000	0.147	0.760	0.970	0.986
	5000	0.000	0.016	1.010	1.000	1.000	0.000	0.045	0.978	1.000	1.000
					No Simultaneity						
$\beta_1 = 0$	200	0.003	0.183	0.889	0.054	0.106	-0.014	2.735	0.973	0.081	0.153
	500	-0.003	0.104	0.980	0.044	0.087	0.017	0.493	0.750	0.066	0.108
	1000	-0.002	0.070	1.021	0.033	0.080	0.009	0.206	0.952	0.053	0.089
	5000	0.001	0.031	1.018	0.046	0.082	0.005	0.084	0.951	0.053	0.107
$\beta_2 = 0.6$	200	-0.036	0.351	0.930	0.351	0.558	-0.051	1.431	1.032	0.131	0.268
	500	0.006	0.215	0.983	0.928	0.962	0.034	0.552	0.674	0.696	0.837
	1000	0.023	0.153	0.982	1.000	1.000	0.034	0.196	0.984	0.984	0.994
	5000	0.028	0.067	1.001	1.000	1.000	0.032	0.079	1.000	1.000	1.000
$\alpha_1 = 0$	200	0.009	0.485	0.781	0.101	0.164	0.022	1.698	1.367	0.115	0.176
	500	0.015	0.260	0.927	0.051	0.112	0.044	0.727	0.947	0.071	0.114
	1000	0.015	0.181	0.934	0.061	0.116	0.015	0.321	0.902	0.051	0.095
	5000	0.002	0.078	0.960	0.057	0.116	0.004	0.127	0.981	0.054	0.106
$\alpha_2 = -0.4$	200	-0.026	0.136	0.944	0.846	0.888	-0.016	0.297	1.338	0.581	0.659
	500	-0.022	0.078	1.025	0.991	0.997	-0.021	0.131	1.158	0.921	0.956
	1000	-0.021	0.056	0.991	1.000	1.000	-0.017	0.078	0.985	0.997	0.999
	5000	-0.021	0.025	0.994	1.000	1.000	-0.021	0.034	0.976	1.000	1.000

Simulated using 1000 replications. **N**: Number of observations
bias: Bias of the estimated coefficient
ssd: Standard Deviation of the estimated coefficients
sse/ssd: Mean of the ratio of the estimated standard error to **ssd**
p5,p10: Probability of rejecting null where coefficient equals 0

Table A2: Simulation Results 2/4

$\lambda_e = 0.25, \lambda_u = 0.25, \gamma = 0.4, \zeta = 0$											
		$Z^A_{i,t}$					$Z^B_{i,t}$				
	N	**bias**	**ssd**	**sse/ssd**	**p5**	**p10**	**bias**	**ssd**	**sse/ssd**	**p5**	**p10**
Main Equation											
$\beta_1 = -0.5$	200	0.019	0.169	0.909	0.864	0.909	0.073	2.614	0.946	0.631	0.708
	500	0.026	0.105	0.932	0.990	0.996	0.011	0.168	0.902	0.838	0.880
	1000	0.027	0.074	0.924	1.000	1.000	0.003	0.102	1.001	0.968	0.980
	5000	0.031	0.033	0.938	1.000	1.000	0.003	0.045	0.981	1.000	1.000
$\beta_2 = 0.6$	200	0.004	0.207	0.928	0.909	0.948	-0.013	0.595	1.262	0.683	0.784
	500	-0.006	0.130	0.945	0.997	0.999	-0.002	0.159	0.967	0.976	0.988
	1000	-0.006	0.094	0.928	1.000	1.000	0.004	0.104	1.006	1.000	1.000
	5000	-0.010	0.042	0.934	1.000	1.000	0.000	0.045	0.993	1.000	1.000
$\alpha_1 = -0.1$	200	0.101	0.469	0.762	0.138	0.187	0.022	1.172	0.647	0.197	0.245
	500	0.140	0.241	0.901	0.056	0.102	0.053	0.487	0.725	0.130	0.173
	1000	0.149	0.174	0.878	0.061	0.125	0.008	0.227	0.955	0.139	0.200
	5000	0.149	0.074	0.920	0.096	0.181	0.001	0.095	0.984	0.227	0.317
$\alpha_2 = -0.4$	200	-0.048	0.084	0.979	0.964	0.981	0.008	0.177	0.958	0.761	0.816
	500	-0.041	0.053	0.963	0.999	1.000	-0.005	0.096	0.965	0.982	0.988
	1000	-0.040	0.037	0.973	1.000	1.000	0.001	0.062	0.977	1.000	1.000
	5000	-0.038	0.017	0.965	1.000	1.000	0.001	0.027	0.965	1.000	1.000
No Simultaneity											
$\beta_1 = 0$	200	0.001	0.093	0.952	0.046	0.109	-0.157	4.698	1.849	0.063	0.117
	500	-0.002	0.056	0.991	0.047	0.091	0.009	0.161	0.897	0.049	0.093
	1000	-0.001	0.038	1.027	0.039	0.084	0.004	0.099	1.006	0.042	0.086
	5000	0.000	0.017	1.012	0.043	0.091	0.002	0.044	0.967	0.057	0.099
$\beta_2 = 0.6$	200	0.011	0.240	0.942	0.854	0.932	-0.118	3.869	1.863	0.629	0.760
	500	0.023	0.147	0.981	0.997	0.999	0.024	0.174	0.971	0.981	0.991
	1000	0.030	0.104	0.981	1.000	1.000	0.033	0.115	1.004	1.000	1.000
	5000	0.030	0.046	0.999	1.000	1.000	0.031	0.050	0.995	1.000	1.000
$\alpha_1 = 0$	200	0.004	0.352	0.852	0.081	0.138	0.056	0.774	0.780	0.080	0.138
	500	0.006	0.202	0.955	0.045	0.096	0.051	0.375	0.912	0.048	0.100
	1000	0.008	0.141	0.964	0.057	0.111	0.011	0.241	0.965	0.052	0.104
	5000	0.001	0.063	0.969	0.058	0.120	0.002	0.104	0.983	0.061	0.109
$\alpha_2 = -0.4$	200	-0.032	0.104	0.965	0.943	0.962	-0.014	0.142	0.918	0.824	0.861
	500	-0.025	0.062	1.025	0.999	1.000	-0.021	0.075	1.018	0.991	0.995
	1000	-0.022	0.045	0.991	1.000	1.000	-0.019	0.053	0.991	1.000	1.000
	5000	-0.021	0.020	0.996	1.000	1.000	-0.020	0.024	0.968	1.000	1.000

Simulated using 1000 replications. **N**: Number of observations
bias: Bias of the estimated coefficient
ssd: Standard Deviation of the estimated coefficients
sse/ssd: Mean of the ratio of the estimated standard error to **ssd**
p5,p10: Probability of rejecting null where coefficient equals 0

Table A3: Simulation Results 3/4

$\lambda_e = 0.5, \lambda_u = 0.5, \gamma = 0.4, \zeta = 0$											
		$Z_{i,t}^A$					$Z_{i,t}^B$				
	N	**bias**	**ssd**	**sse/ssd**	**p5**	**p10**	**bias**	**ssd**	**sse/ssd**	**p5**	**p10**
Main Equation											
$\beta_1 = -0.5$	200	0.047	0.103	0.863	0.990	0.993	0.010	0.258	0.692	0.816	0.860
	500	0.061	0.067	0.838	1.000	1.000	0.008	0.104	0.906	0.965	0.975
	1000	0.065	0.047	0.853	1.000	1.000	0.003	0.065	0.997	1.000	1.000
	5000	0.069	0.022	0.834	1.000	1.000	0.001	0.029	0.997	1.000	1.000
$\beta_2 = 0.6$	200	-0.016	0.151	0.873	0.993	0.996	-0.002	0.170	0.972	0.923	0.956
	500	-0.039	0.097	0.877	1.000	1.000	-0.002	0.098	0.978	0.999	1.000
	1000	-0.044	0.070	0.864	1.000	1.000	0.002	0.066	1.002	1.000	1.000
	5000	-0.051	0.032	0.854	1.000	1.000	0.000	0.029	0.982	1.000	1.000
$\alpha_1 = -0.1$	200	0.268	0.447	0.735	0.077	0.125	0.076	0.779	0.712	0.171	0.205
	500	0.317	0.253	0.847	0.094	0.198	0.037	0.321	0.883	0.126	0.165
	1000	0.324	0.181	0.837	0.254	0.375	0.004	0.188	0.989	0.151	0.217
	5000	0.334	0.080	0.854	0.932	0.964	0.001	0.083	0.979	0.268	0.371
$\alpha_2 = -0.4$	200	-0.066	0.078	0.944	0.990	0.996	-0.003	0.122	0.956	0.906	0.938
	500	-0.055	0.051	0.933	1.000	1.000	-0.003	0.065	1.010	0.998	0.999
	1000	-0.052	0.036	0.930	1.000	1.000	0.001	0.046	0.987	1.000	1.000
	5000	-0.047	0.016	0.927	1.000	1.000	0.001	0.021	0.962	1.000	1.000
No Simultaneity											
$\beta_1 = 0$	200	-0.001	0.051	0.986	0.048	0.103	0.010	0.221	0.721	0.062	0.096
	500	-0.001	0.033	0.962	0.052	0.118	0.007	0.090	0.931	0.046	0.099
	1000	0.000	0.022	1.014	0.045	0.094	0.004	0.059	0.991	0.044	0.090
	5000	0.000	0.010	0.994	0.051	0.101	0.001	0.026	1.001	0.056	0.094
$\beta_2 = 0.6$	200	0.033	0.158	0.947	0.992	0.998	0.023	0.191	0.968	0.931	0.952
	500	0.029	0.097	0.976	1.000	1.000	0.026	0.110	0.976	1.000	1.000
	1000	0.031	0.068	0.987	1.000	1.000	0.032	0.075	0.996	1.000	1.000
	5000	0.030	0.030	0.992	1.000	1.000	0.031	0.033	0.982	1.000	1.000
$\alpha_1 = 0$	200	0.000	0.277	0.906	0.075	0.132	0.058	0.577	0.835	0.066	0.124
	500	0.002	0.166	0.977	0.044	0.097	0.039	0.310	0.948	0.052	0.098
	1000	0.004	0.117	0.980	0.061	0.105	0.006	0.205	0.992	0.049	0.096
	5000	0.002	0.053	0.971	0.056	0.114	0.001	0.092	0.979	0.054	0.117
$\alpha_2 = -0.4$	200	-0.033	0.084	0.970	0.982	0.990	-0.019	0.105	0.944	0.935	0.959
	500	-0.026	0.050	1.029	1.000	1.000	-0.021	0.059	1.021	0.999	1.000
	1000	-0.023	0.037	0.997	1.000	1.000	-0.020	0.042	0.994	1.000	1.000
	5000	-0.021	0.016	1.014	1.000	1.000	-0.020	0.019	0.976	1.000	1.000

Simulated using 1000 replications. **N**: Number of observations
bias: Bias of the estimated coefficient
ssd: Standard Deviation of the estimated coefficients
sse/ssd: Mean of the ratio of the estimated standard error to **ssd**
p5,p10: Probability of rejecting null where coefficient equals 0

Table A4: Simulation Results 4/4

		$Z_{i,t}^{A}$					$Z_{i,t}^{B}$				
$\lambda_e = 0.5, \lambda_u = 0.5, \gamma = 0.4, \zeta = -0.1$	**N**	**bias**	**ssd**	**sse/ssd**	**p5**	**p10**	**bias**	**ssd**	**sse/ssd**	**p5**	**p10**
Main Equation											
$\beta_1 = -0.5$	200	-0.014	0.103	0.873	0.996	0.998	0.010	0.194	0.838	0.795	0.844
	500	0.001	0.067	0.850	1.000	1.000	0.010	0.108	0.880	0.961	0.968
	1000	0.005	0.047	0.866	1.000	1.000	0.004	0.066	0.987	0.998	1.000
	5000	0.009	0.022	0.853	1.000	1.000	0.001	0.028	1.004	1.000	1.000
$\beta_2 = 0.6$	200	-0.026	0.137	0.898	0.993	0.994	0.004	0.165	0.986	0.932	0.968
	500	-0.051	0.091	0.878	1.000	1.000	-0.001	0.101	0.960	0.995	0.997
	1000	-0.054	0.065	0.874	1.000	1.000	0.002	0.067	0.989	1.000	1.000
	5000	-0.060	0.029	0.872	1.000	1.000	0.000	0.030	0.980	1.000	1.000
$\alpha_1 = -0.1$	200	0.297	0.467	0.775	0.068	0.130	0.062	1.005	0.579	0.167	0.221
	500	0.365	0.287	0.841	0.090	0.219	0.040	0.362	0.801	0.140	0.200
	1000	0.377	0.200	0.854	0.307	0.442	0.008	0.192	0.985	0.158	0.225
	5000	0.386	0.087	0.881	0.975	0.986	0.000	0.084	0.984	0.283	0.377
$\alpha_2 = -0.4$	200	-0.113	0.076	0.952	0.997	0.999	-0.005	0.131	0.916	0.925	0.949
	500	-0.104	0.049	0.947	1.000	1.000	-0.003	0.068	0.983	0.995	0.997
	1000	-0.102	0.034	0.960	1.000	1.000	-0.001	0.046	1.000	1.000	1.000
	5000	-0.098	0.016	0.916	1.000	1.000	0.001	0.021	0.970	1.000	1.000
No Simultaneity											
$\beta_1 = 0$	200	-0.069	0.052	0.956	0.324	0.445	0.014	0.177	0.821	0.081	0.127
	500	-0.068	0.032	0.958	0.584	0.691	0.009	0.093	0.917	0.049	0.101
	1000	-0.067	0.022	0.985	0.841	0.904	0.004	0.060	0.983	0.051	0.099
	5000	-0.067	0.010	0.973	1.000	1.000	0.001	0.026	1.010	0.045	0.100
$\beta_2 = 0.6$	200	0.000	0.140	0.941	0.995	0.998	0.028	0.184	0.973	0.936	0.963
	500	-0.010	0.087	0.956	1.000	1.000	0.027	0.111	0.963	0.999	0.999
	1000	-0.010	0.060	0.982	1.000	1.000	0.032	0.075	0.986	1.000	1.000
	5000	-0.011	0.027	0.983	1.000	1.000	0.031	0.033	0.980	1.000	1.000
$\alpha_1 = 0$	200	0.049	0.286	0.897	0.073	0.139	0.057	0.549	0.852	0.063	0.117
	500	0.061	0.169	0.984	0.117	0.210	0.035	0.322	0.900	0.054	0.119
	1000	0.066	0.117	1.004	0.245	0.370	0.011	0.201	0.995	0.042	0.091
	5000	0.065	0.052	1.011	0.901	0.946	0.000	0.090	0.989	0.049	0.101
$\alpha_2 = -0.4$	200	-0.066	0.080	1.015	0.995	1.000	-0.021	0.103	0.956	0.945	0.969
	500	-0.060	0.049	1.061	1.000	1.000	-0.021	0.061	0.995	0.997	0.999
	1000	-0.059	0.035	1.046	1.000	1.000	-0.021	0.042	1.000	1.000	1.000
	5000	-0.057	0.016	1.038	1.000	1.000	-0.020	0.019	0.984	1.000	1.000

Simulated using 1000 replications. **N**: Number of observations
bias: Bias of the estimated coefficient
ssd: Standard Deviation of the estimated coefficients
sse/ssd: Mean of the ratio of the estimated standard error to **ssd**
p5,p10: Probability of rejecting null where coefficient equals 0

C. Tables

Table A5: Individual Income and Household Income Per Capita

	Assumptions A	Assumptions B	
	CES-D	**CES-D**	**CES-D**
	(1)	(2)	(3)*
hhincome_percapita_t	-0.00123	-0.0033***	-0.0034**
	(0.00078)	(0.00118)	(0.00150)
hhincome_percapita^2_t	0.00000***	0.00000***	0.00000***
	(0.00)	(0.00)	(0.00)
individualincome_t	-0.00005	0.00094	0.00095
	(0.00040)	(0.00077)	(0.00081)
individualincome^2_t	-0.00005	0.00094	0.00095
	(0.00)	(0.00)	(0.00)
CES-D_(t-1)	-0.414	0.0298	-0.541
	(0.223)	(0.655)	(0.599)
Controls	Yes	Yes	Yes
Observations	4,173	4,173	2,708

Cluster robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Controls include household size and marital status.
*Results from (3) restrict the sample to those who are economically active.
Including both household income per capita and individual income as regressors (instrumented by lagged levels) shows that household income per capita plays a more important role in determining psychological well-being.

Table A6: Estimates for Figure 4 and robustness checks for the sample selection

	CES-D in Wave 3												
	1	2	3	4	5	6	7	8	9	10	11	12	13
ΔCES-D$\leq$ 3	392.2***	735.2**	121.3	141.9	-51	-309	103.8	369.1	-666.4	-602.9**	-509.3**	-680.1***	-724.8**
	(102.8)	(373.7)	(443.3)	(358.3)	(518.2)	(499.7)	(453.3)	(617.6)	(438.7)	(282.1)	(220.9)	(181.8)	(327.8)
ΔCES-D$\leq$ 4*	326.6***	639.8***	345	321.4	-83.7	-333.8	-229.6	-250.1	-529.6***	-441.5***	-347.7***	-304.7***	-422.2***
	(85.7)	(208.1)	(241.8)	(257.7)	(381.3)	(399.7)	(329.5)	(323.2)	(185.7)	(110.9)	(95.6)	(83.2)	(119.1)
ΔCES-D$\leq$ 5	351.7***	496.4***	278.1***	184.7	-36.8	-119.5	-201.1	-366.4	-375.1**	-290.5***	-152.2**	-190.6***	-308.1***
	(103.4)	(174.2)	(105.7)	(183.9)	(317.6)	(434.8)	(275.6)	(246.1)	(148.6)	(78.6)	(59.6)	(49.3)	(61.3)

Cluster robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1
Controls include household size and marital status.
Results shown without correction for multiple testing. Including in the sample those who experience larger changes increases the sample decreased the magnitude of the estimated marginal effects, however these estimates are become less and less marginal. However, the threshold is clearly evident for different specifications.

Table A7: Estimates for Figures 6-9

	Wave 3 Household Income Per Capita Decile									
	1	2	3	4	5	6	7	8	9	10
	Dependent Variable CES-D									
hhincome_percapita_t	-0.0038***	-0.0026***	-0.00211***	-0.00148**	-0.00067	-0.00015	0.00023	0.00026	0.00057**	0.00068**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Log(hhincome_percapita_t)	-1.467***	-1.39477***	-1.492***	-1.298**	-0.784	-0.166	0.587	0.779	2.777*	0.905
	(0.417)	(0.460)	(0.498)	(0.580)	(0.688)	(0.734)	(0.969)	(1.394)	(1.478)	(1.385)
foodexp_percapita_t	-0.021***	-0.0199***	-0.0187***	-0.0142***	-0.0072**	-0.002	-0.00003	-0.00096	0.00058	0.0050*
	(0.007)	(0.005)	(0.005)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.003)
Log(foodexp_percapita_t)	-2.66***	-2.89***	-3.123***	-2.71***	-1.67**	-0.843	-0.491	-0.102	0.202	4.50**
	(0.92)	(0.84)	(0.94)	(0.97)	(0.84)	(0.84)	(1.02)	(1.26)	(1.25)	(2.24)
	Dependent Variable: Life Satisfaction									
Log(hhincome_percapita_t)	1.15***	1.47***	1.53***	0.96***	1.01**	1.69***	1.38***	2.44***	1.25*	1.38
	(0.26)	(0.25)	(0.27)	(0.31)	(0.41)	(0.40)	(0.47)	(0.70)	(0.71)	(0.86)
	Dependent Variable: Self-reported happiness									
Log(hhincome_percapita_t)	0.102***	0.141***	0.186***	0.231***	0.280***	0.196***	0.229***	0.285**	0.291	0.251
	(0.035)	(0.039)	(0.046)	(0.048)	(0.070)	(0.072)	(0.066)	(0.131)	(0.180)	(0.207)

Cluster robust standard errors in parentheses: *** $p<0.01$, ** $p<0.05$, * $p<0.1$
Controls include household size and marital status.
Results shown without correction for multiple testing. Including in the sample those who experience larger changes increases the sample decreased the magnitude of the estimated marginal effects, however these estimates are become less and less marginal. However, the threshold is clearly evident for different specifications.

Table A8: Testing Predictions of Simulations

Wave 4	$\mathrm{Poor_t}$ (1)
$Poor_{t\text{-}3}$	0.047***
	(0.0168)
$HighCES\text{-}D_{t\text{-}3}$	-0.0061
	(.0116)
$Poor_{t\text{-}3}$*$HighCES\text{-}D_{t\text{-}3}$	0.056***
	(.0194)
Controls	Yes
N	10,671
R-Squared	0.3139

Cluster robust standard errors in parentheses: *** p<0.01, ** p<0.05, * p<0.1 Controls include age, age squared, sex, region, employment status, education levels, language, race, and perceived health.

D. Figures

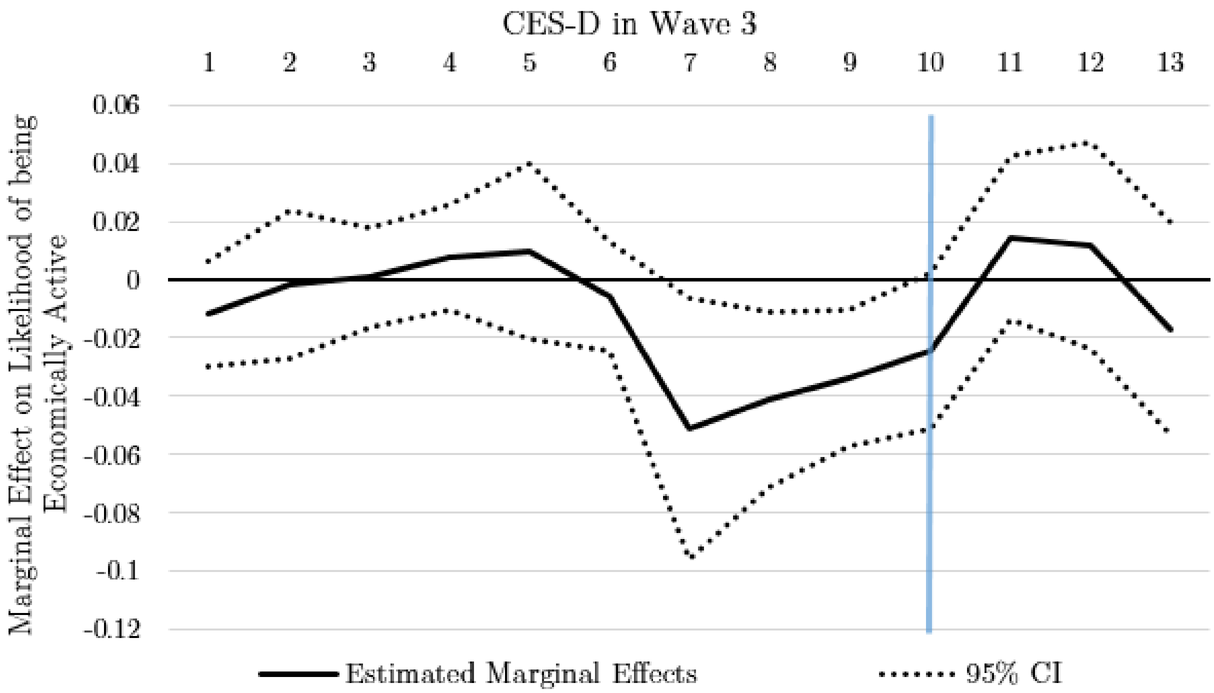

Figure A1: Testing for nonlinearity in the effect of CES-D on economic activity shows similar patterns to individual income.

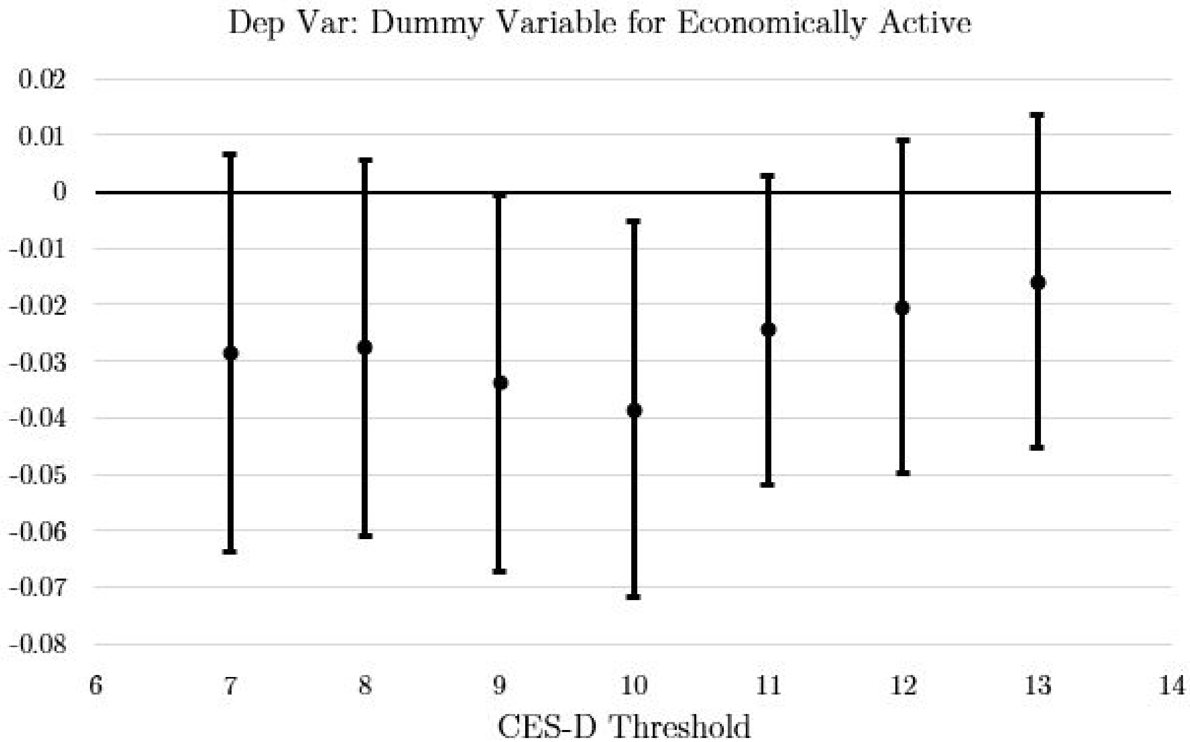

Figure A2: Marginal effects curve for economic active shows a similar pattern to individual income, however the effects seem to start a little earlier in CES-D scale.

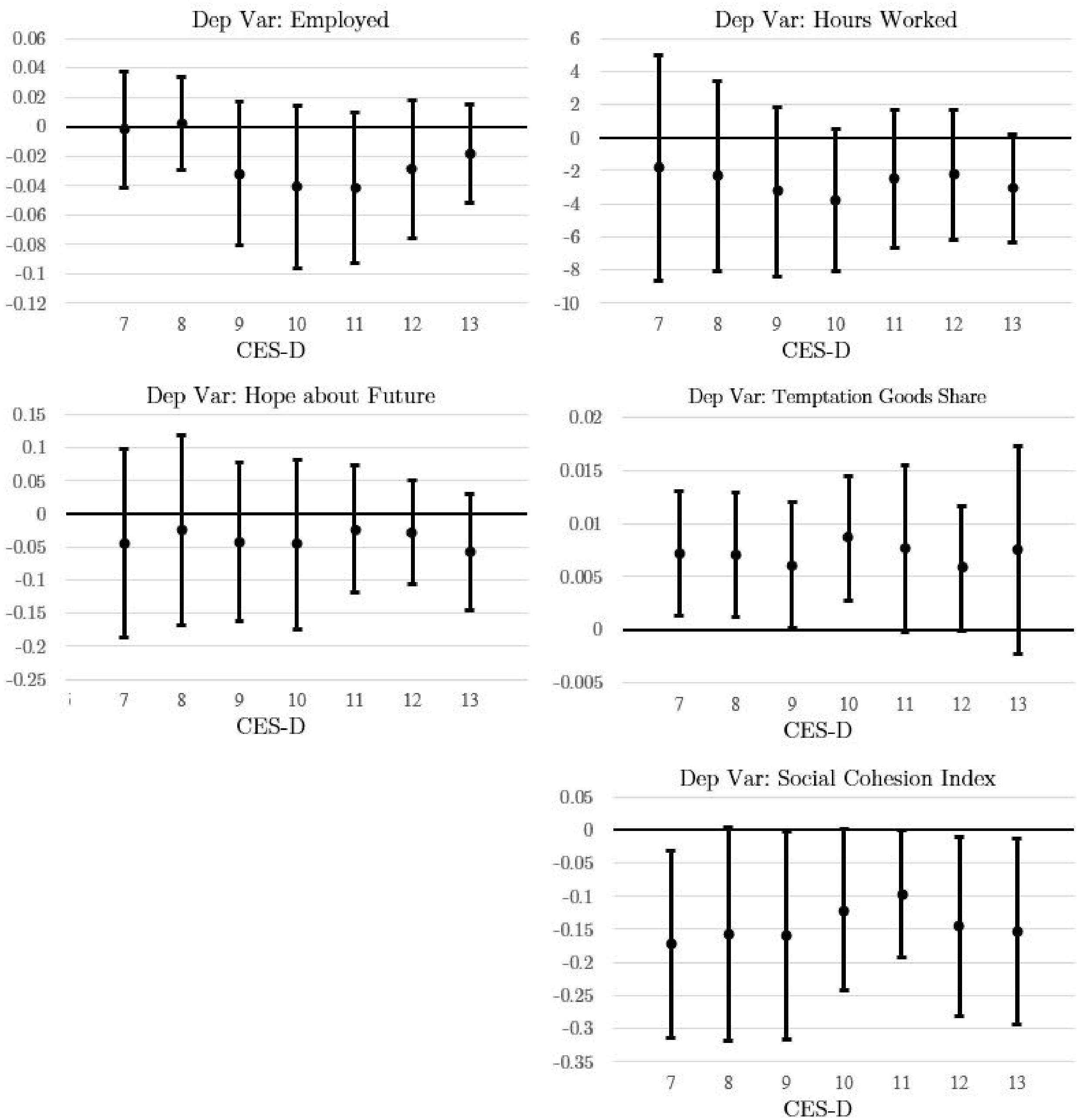

Figure A3: Although not always achieving statistical significance, the mechanisms show similar threshold patterns.

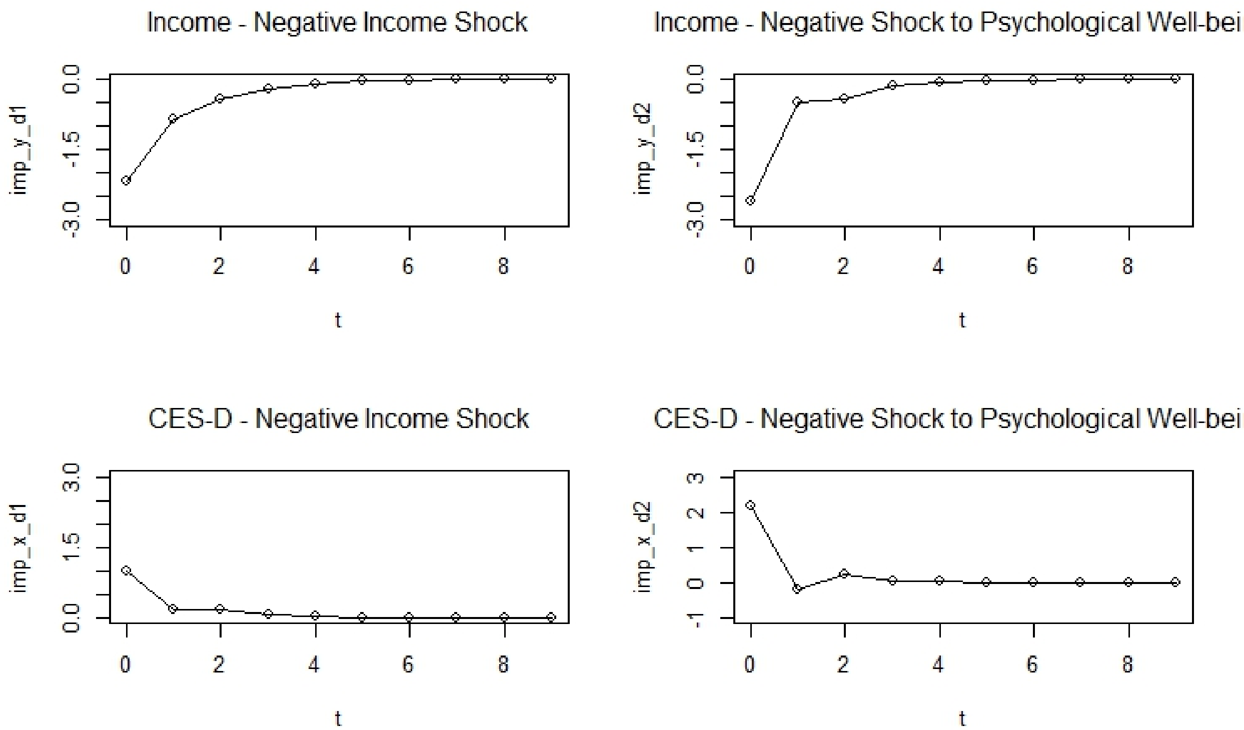

Figure A4: Impulse Response Functions for both shocks and both variables