Permanent Income and Subjective Well-Being

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Abstract

We provide a new explanation for the stronger relationship between income and subjective wellbeing (SWB) found in cross-sectional versus panel studies based on the predictions of a rational expectations model of utility maximization with permanent and transitory income shocks. The model predicts that SWB is affected by unanticipated rather than anticipated income shocks, and is more influenced by permanent rather than transitory income shocks. We confirm the model predictions empirically by analyzing panel data from China, and show that differences in the relative importance of permanent income can explain the stronger (weaker) impact of income often found in cross-sectional (panel) estimation. We also empirically confirm asymmetric impacts of positive and negative transitory income shocks as predicted by a model with credit constraints.

Key words: subjective well-being, permanent income, transitory income

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1. Introduction

Will more money bring happiness? This question has received a great deal of attention from economists in recent years, but a definitive answer remains elusive. Studies that analyze individual-level cross-sectional data consistently find that life satisfaction or happiness significantly increases with income, even after controlling for other factors (Blanchflower and Oswald, 2004; Shields and Price, 2005; Graham and Pettinato, 2004; Lelkers, 2006; Carroll et al., 2009; Clark et al., 2005; Di Tella et al., 2003; Frey and Stutzer, 2002). However, evidence from individual-level panel data suggests a much weaker relationship both in magnitude and significance (Winkelmann et al., 1998; Ferrer-i-Carbonell and Frijters, 2004; Luttmer, 2005; Layard et al., 2008).

Theoretical explanations for this difference have mainly been psychological. According to the relative income hypothesis (RIH), people care about relative rather than absolute income, so that subjective well-being (SWB) increases with own income and decreases with the average income of one’s reference group (Duesenberry, 1949; Pollak, 1976; Easterlin 1973, 1974, 1995; Clark et al., 2008). At a given point in time, average income is fixed so individual subjective well-being (SWB) increases sharply with own income. However, over time the positive effect of increases in own income may be offset by the negative effect of increasing average incomes.1

This paper provides a new explanation for the seemingly contradictory relationships between income and SWB found in individual cross-sectional and panel analysis, and provides empirical evidence to support it. Our main argument is that an individual’s SWB

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1 Another psychological explanation for the lack of increases in happiness with income growth is that people’s assessment of life satisfaction depends on the discrepancy between their aspirations (which rise with income) and their actual income (Easterlin, 2001; Stutzer, 2004). However, the aspiration-adaptation hypothesis (AAH) can only explain the more positive relationship found in cross-sectional comparisons by making strong assumptions that may be unrealistic, for example that at a fixed point in time aspirations are fairly similar among income groups (Easterlin, 2001) or the relative gap between income aspirations and actual income is smaller for rich people (Stutzer, 2004). Empirical tests of the AAH are inconclusive (Di Tella et al., 2010; Gardner and Oswald, 2007).
measured at any point in time is most influenced by his or her permanent income, and previous empirical studies do not adequately take into account how different components of income, in particular expected versus unexpected income shocks and permanent versus transitory income, may affect SWB differently. Doing so can reconcile the seemingly contradictory findings of cross-sectional and panel studies using microdata.

This study does not necessarily undermine the importance of relative income or wealth for SWB (Clark et al., 2008; Headey et al., 2004). Rather, it emphasizes the independent role of permanent income on SWB, apart from relative income or wealth, and its ability to explain the stronger (weaker) impact of income often found in cross-sectional (panel) studies. Our findings are not directly related to but could inform debates over the Easterlin Paradox—the claim that the relationship between GDP and SWB is stronger when one looks at a cross-section of counties than when one examines changes in SWB within countries over time (Easterlin, 1974, 1995).² Because the relative importance of the permanent and transitory components of GDP in cross-section and over time may be different than for individual incomes and be imperfectly correlated with levels of (and changes in) individual incomes for those living in a country, there is no reason to necessarily expect that differences in cross-country versus within-country correlations between SWB and GDP will be the same as differences between SWB and individual incomes within a country. For example, if unexpected permanent shocks explain a relatively larger share of GDP changes than individual income changes, then it would not be surprising if cross-sectional versus over-time correlations between SWB and GDP were more consistent than for individual income, as suggested by Sacks, Stevenson and Wolfers (2010a and 2010b). Exploring these connections empirically is an exciting line for future research.

² Sacks, Stevenson and Wolfers (2010a, 2010b) provide evidence using data from many countries and time periods that the relationship between SWB and GDP among countries and within countries over time are positive and consistent in magnitude (no paradox), while Easterlin (2015) argues that within-country associations do not persist over the long term.
In this study, we define SWB at a point in time as measured by global life satisfaction to reflect expected lifetime utility, equal to current plus discounted future expected utility. Our hypothesis accounts for the fact that money plays purely an instrumental role, affecting utility only by enabling greater consumption of goods and services (Veenhoven, 1991). From this perspective, only differences or changes in income that strongly affect current and future consumption are likely to influence SWB. In the simple dynamic model assuming quadratic utility presented below, consumption in any period is exactly equal to expected future consumption and annualized permanent income, which highlights the notion that only the permanent component of income matters for well-being. Defining SWB to reflect expected utility from current and future consumption enables us to directly apply (we believe for the first time) insights from a large theoretical and empirical literature on the permanent income hypothesis (PIH) to explain and test how income affects SWB.

In permanent income models of consumption, people smooth their consumption (and utility) over time by saving extra income during good years and drawing down savings or borrowing during bad years. The optimal level of consumption in each period thus depends on the level of permanent income (Friedman, 1957). In addition, for people with rational expectations, only unexpected income shocks affect consumption choices. Finally, adjustments of consumption are much greater for permanent income shocks than for transitory income shocks. When shocks have persistent effects on future income flows, such as an accident creating permanent disability, people immediately adjust their level of consumption proportionally (Meyer and Mok, 2013). If an income shock lasts only one period, e.g., winning a lottery, people will save most of the income rather than consume it.
immediately. Many empirical studies have found behavior consistent with these predictions of the permanent income hypothesis.\(^3\),\(^4\)

The above insights can explain the inconsistent findings in the literature on the relationship between income and SWB in cross-sectional and panel analysis. In cross-sectional comparisons, a large share of income differences reflect differences in lifetime (or permanent) income, with differences associated with transitory shocks being relatively less important. However, when empirically examining the impact of changes in an individual’s income over time using panel data, only unanticipated permanent income shocks are expected to have a large effect on consumption and well-being, which account for a relatively small share of income changes compared to anticipated income changes and unanticipated transitory income shocks. For this reason it is natural to expect a smaller effect of income on SWB in panel analysis than in cross-sectional analysis.\(^5\)

To provide empirical support for our explanation, we conduct for the first time an empirical analysis of the impact on SWB of permanent versus transitory income shocks using panel household survey data from China. The lack of previous studies may reflect limitations of most datasets, either due to lack of systematic measurements of SWB or an inability to distinguish clearly between different types of income shocks. The data set used in this study is the only data set of which we are aware that includes both measurements of SWB and income expectations, which are necessary to separately measure both expected income and

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\(^3\) These studies do not examine the relationship between income and happiness or life satisfaction using individual panel data. In this sense, this study extends further the rapidly expanding use of SWB measurements in economic studies (Di Tella and MacCulloch, 2006).

\(^4\) Studies of the effect of anticipated income changes such as expenditure changes from extra wage payments or paying college tuition on consumption confirm consumption smoothing behavior (Browning and Collado, 2001; Souleles, 2000). Studies examining the response of consumption to unanticipated income shocks also generally support the permanent income hypothesis. For example, Hall and Mishkin (1982) find temporary income tax policies have a smaller effect on consumption than more permanent income changes in the US, Paxson (1992) finds a higher marginal propensity to save out of transitory income due to rainfall shocks than permanent income among rural households in Thailand, and Pistaferri (2001) finds greater savings of transitory income than permanent income shocks in Italy. Earlier studies finding excess sensitivity of consumption to income (Hall, 1978; Flavin, 1981) did not use a robust methodology for predicting anticipated income (Jappelli and Pistaferri, 2010).

\(^5\) This explanation is distinct from the argument that variation in panel data has a smaller signal to noise ratio than in cross-sectional data (discussed further below).
unexpected transitory and permanent income shocks. This is what enables us to provide new empirical evidence on how income affects SWB.

To separately identify different types of income shocks, we combine information on income realizations and subjective expectations of income (Hayashi, 1985; Pistaferri, 2001; Kaufmann and Pistaferri, 2009). Meghir and Pistaferri (2011) explain the advantages of this approach in comparison to those that rely on natural experiments or year-to-year unexplained volatility in income. First, the method does not require the estimation of an income process, and permanent and transitory income shocks can be identified even with short panels. Second, as the expectation of future income is revealed by respondents themselves, there is no problem of “superior information” of respondents compared to the econometrician (Flavin, 1993). Lastly, the approach encompasses all possible types of income shocks rather than relying on a single wealth or income shock based on a quasi-experiment.

The rest of the paper is organized as follows. In Section 2, we present a theoretical model to derive predictions to be taken to the data. Section 3 discusses the empirical strategy for separately identifying the impacts of permanent and transitory income shocks, and shows how to decompose income into its component parts to better understand the reasons for differences in results of cross-sectional and panel regressions of SWB on income. Section 4 describes the data source and variable construction. Section 5 presents the empirical results. Section 6 presents results of extensions of the benchmark model, and Section 7 provides several robustness checks. A final section concludes.

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6 The data sets that have been used in studies of SWB, such as the British Household Panel Survey (BHPS), the German Socio-Economic Panel (GSOEP), the Household, Income and Labour Dynamics in Australia (HILDA), the Socio-Economic Panel Survey in the Netherlands, and the Russia Longitudinal Monitoring Survey, do not include questions on expectations of future income. Some of them do ask a question about the respondent’s expectation of income changes (better/worse off), but this is insufficient to quantify expected future income. The only data set of which we are aware that includes questions on income expectations is the Survey of Household Income and Wealth (SHIW) in Italy, in its 1989 and 1991 waves, but the SHIW did not include measurements of SWB.
2. Theoretical Model

Consider the following utility maximization problem to determine optimal consumption:

$$
\text{Max } U_t = E_t \left[ \sum_{s=0}^{\infty} \beta^s u(c_{t+s}) \right]
$$

subject to an intertemporal budget constraint:

$$
w_{t+s+1} = (1 + r)w_{t+s} + x_{t+s} - c_{t+s}, \ \forall \ s \geq 0.
$$

Here, $w$ is wealth, $x$ is income, $c$ is consumption, and $\beta$ is the discount factor. We assume that $w_t$ and $x_{t+s}$ ($\forall \ s \geq 0$) are exogenously given. Without loss of generality, we assume the limit of $(1 + r)^{-t}w_t$ to be zero as $t$ tends to infinity to rule out any Ponzi games, and that individuals can trade assets freely at the fixed real interest rate $r$. The solution is the familiar Euler equation:

$$
u'(c_t) = \beta(1 + r)E_t[u'(c_{t+1})].
$$

By assuming quadratic preferences ($u(c) = c - (b/2)c^2$) and that the rate of time preference is equal to one plus the interest rate ($\beta(1 + r) = 1$), we derive a simple expression for optimal consumption (Hall, 1978):

$$
E_t c_{t+1} = c_t. \tag{1}
$$

In words, the forecast of optimal consumption in the next period equals current consumption, so that current consumption captures both current utility and expected future utility. Equation (1) implies that a change in consumption from $t$ to $t + 1$ cannot be predicted on the basis of information available at time $t$. Applying (1) forward through time, we have $E_t c_{t+s} = c_t$ for all $s > 1$.

Using $E_t c_{t+s} = c_t$ and aggregating the intertemporal budget constraints, we can derive the following expression for consumption:

$$
c_t = r \left[ w_t + \sum_{s=0}^{\infty} \left( \frac{1}{1+r} \right)^{s+1} E_t x_{t+s} \right] = y_t^P. \tag{2}
$$

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7 We later consider versions of the model with a finite time horizon and with liquidity constraints.
\( y_t^p \) is defined as the annual value of total resources, consisting of current wealth, \( w_t \), and current and future income flows \( \{x_{t+s}\}, s = 0, 1, 2, \ldots, \infty \). We call \( y_t^p \) the *permanent income* at time \( t \). Equation (2) implies that consumption changes one-to-one with changes in permanent income.

Furthermore, by substituting the intertemporal budget constraint at time \( t \) into (2), and reorganizing terms, we can derive the following equation:

\[
(3)
\]

Equation (3) indicates that only unexpected innovations of future income arriving at time \( t + 1 \) will cause consumption at time \( t + 1 \) to deviate from consumption at time \( t \). In other words, people adjust their consumption instantly when they learn any news about changes in future income. They make no further adjustments when the changes actually happen.

According to equation (3), changes in consumption are determined by innovations in expectations about future income. Therefore, modeling the income process is crucial for predicting consumption choices and SWB. Following a widely used formulation, we define the income process as the sum of a random walk and white noise (e.g., Meghir and Pistaferri, 2011):

\[
(4)
\]

\[
(5)
\]

For all \( s \) and \( t \), \( \delta_s \) and \( \eta_t \) are independent. The appeal of the above income process is that it helps us to distinguish between the impact of transitory income shocks (defined as \( \delta_t \)) and permanent income shocks (defined as \( \eta_t \)).

By substituting (4) and (5) into (3), we get the following expression for changes in consumption:

\[
(6)
\]
Since \( r > 0, \frac{r}{1+r} < 1 \). Thus, the marginal propensity to consume (MPC) is greater for a permanent income shock than for a transitory income shock.

Because of the equivalence result that consumption in any period equals expected consumption in future periods, it is straightforward to show that if we define subjective well-being to be the sum of current and future discounted utility (\( V_t \)), the relative impacts of permanent income shocks and transitory income shocks on changes in subjective well-being will be the same as their relative impacts on changes in consumption (Appendix 1). We can also show that the result that permanent income shocks have a greater impact than transitory income shocks on subjective well-being (defined as current plus future discounted utility) does not require that we assume quadratic utility but is also robust to assuming that the utility function exhibits constant relative risk aversion (CRRA) (Appendix 2).

3. Empirical Strategy

As mentioned earlier, one of the difficulties in identifying different types of income shocks is that consumers generally have “superior information” to econometricians. We follow earlier research that uses responses to questions about subjective expectations to overcome this problem and distinguish permanent income shocks from transitory income shocks (Pistaferri, 2001).

The income process described in equations (4) and (5) can be rewritten as follows:

\[ x_{t+1} = x_t + \eta_{t+1} + \delta_{t+1} - \delta_t \]

An unanticipated income shock at time \( t + 1 \) can be identified by the difference between income realizations and prior income expectations. That is,

\[ x_{t+1} - E_t(x_{t+1}) = \eta_{t+1} + \delta_{t+1}. \]  

(7)

\( E_t(x_{t+1}) \) is the expectation of income in period \( t + 1 \) based on the individual’s information at time \( t \). Since the permanent component of income is a random walk, the expected future
income at time t is equal to the permanent component of current income ($x_t^p$). Thus, from equation (4) we know $E_t(x_{t+1}) = x_t - \delta_t$. Using this identity and equation (7), it is straightforward to derive the following:

$$E_{t+1}(x_{t+2}) - E_t(x_{t+1}) = \eta_{t+1}. \tag{8}$$

The transitory income shock can be identified from (7) and (8) as follows:

$$x_{t+1} - E_{t+1}(x_{t+2}) = \delta_{t+1}. \tag{9}$$

We are now ready to specify an equation to estimate the predictions of the rational expectation-permanent income hypothesis (RE-PIH) as implied by equation (6), namely that changes in SWB are affected by unanticipated shocks and that an unanticipated permanent income shock has a greater impact on well-being than a transitory income shock. Following equation (6), we thus regress change in SWB on the empirical measures of the permanent and transitory income shocks derived in equations (8) and (9):

$$\Delta s_{i,t+1} = \beta_0 + \beta_1 [E_{t+1}(x_{i,t+2}) - E_t(x_{i,t+1})] + \beta_2 [x_{i,t+1} - E_{t+1}(x_{i,t+2})] + \psi Z_{i,t+1} + \zeta_{i,t+1}, \tag{10}$$

where $\Delta s_{i,t+1}$ is the change in SWB of individual i between $t+1$ and $t$, $E_{t+1}(x_{i,t+2}) - E_t(x_{i,t+1})$ is the permanent income shock at $t+1$, and $x_{i,t+1} - E_{t+1}(x_{i,t+2})$ is the transitory income shock at $t+1$. We also include a set of control variables $Z_{i,t+1}$ which are described later, and $\zeta_{i,t+1}$ is the error term. Our hypotheses is that $\beta_1 > \beta_2$.

In our data, subjective income expectations are measured as the household’s expected relative income (and wealth) position in the village while the income realization is measured as the log of household income per capita (measurement explained in more detail in section 4). To make the actual and relative income measures more comparable, we convert household income per capita into a measure of relative income status in the village by ranking it among the households in each village. We then adjust our specification to accommodate the available measurements. Consider the following linear model of relative income position:
\[ r_{i,t} = \alpha_0 + \alpha_1 x_{i,t} + \alpha_2 X_{i,t}, \]

where \( r_{i,t} \) is the relative income position of individual \( i \) at time \( t \) in his or her village \( j \), \( x_{i,t} \) is the income realization of individual \( i \) at time \( t \), and \( X_{i,t} \) is the average income of all villagers in village \( j \). By construction, \( \alpha_1 > 0 \) and \( \alpha_2 < 0 \).

At time \( t \), the expectation of individual \( i \) of his relative income status at time \( t + 1 \) can be written as follows:

\[
E_{i,t}(r_{i,t+1}) = \alpha_0 + \alpha_1 E_{i,t}(x_{i,t+1}) + \alpha_2 E_{i,t}(X_{i,t+1}).
\]

Expected income position is determined by one’s expectation of own income and by one’s expectation of average income in the village. By assuming \( E_{i,t}(X_{j,t+1}) = E_t(X_{j,t+1}) \), or that villagers share the same information set about future economic status of village, we get:

\[
r_{i,t+1} - E_{i,t}(r_{i,t+1}) = \alpha_1 [x_{i,t+1} - E_{i,t}(x_{i,t+1})] + \alpha_2 V_j,
\]

where \( V_j = X_{j,t+1} - E_t(X_{j,t+1}) \). The above equation indicates how unexpected income shocks are related to unexpected changes in the household’s relative income status.

Substituting the above equation into (10), we derive our main empirical specification to directly test the predictions of the theoretical model:

\[
\Delta s_{i,t+1} = \beta_0' + \beta_1'[E_{i,t+1}(r_{i,t+2}) - E_{i,t}(r_{i,t+1})] + \beta_2'[r_{i,t+1} - E_{i,t+1}(r_{i,t+2})] + V_j' + \psi' Z_{i,t+1} + \zeta_{i,t+1},
\]

where \( \beta_1' = \frac{\beta_1}{\alpha_1}, \beta_2' = \frac{\beta_2}{\alpha_1}, V_j' = -\alpha_2 [\beta_1'E_{t+1}(X_{j,t+2}) - \beta_1'E_t(X_{j,t+1}) + \beta_2'V_j]. \)

Again, we are interested in testing whether \( \beta_1' > \beta_2' \). In the regressions, \( V_j' \) is absorbed by village dummies. Because the subjective relative income measures are based on a question that actually refers to both income and wealth, we also add control variables for wealth in all regressions that

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8 The expectation of future income may reflect the life-cycle pattern in income which usually has an inverse U-shape. We therefore replace the change in income expectations by the residual from its regression on age and age squared, or the residual from its regression on the interactions of age controls with gender, education, and village fixed effects to account for heterogeneity in expected age-earnings profiles. The results are robust to these adjustments, which are available upon request.
employ such measures in order to better isolate the impact of relative income. The results are robust to excluding the wealth variables.

To investigate how distinguishing between permanent and transitory income shocks can explain the different results of typical cross-sectional and panel regressions, we can start with the conventional specifications and in each regression decompose the income variable into its component parts and test how each component affects subjective well-being. Consider a typical cross-sectional regression equation for the determinants of SWB:

$$ s_{it} = \phi_0 + \phi x_{it} + \Theta Z_{it} + e_{it}, $$

where $x_{it}$ is the income of individual $i$ at time $t$, and $Z_{it}$ is a set of control variables. As shown in equation (4), income can be defined to be the sum of transitory income shocks ($\delta_{it}$) and lifetime income at time $t$ ($x_{it}^R$) (Hall and Mishkin, 1982). The theoretical model suggests that we should account for the different role of transitory and permanent income on well-being, for example by estimating the following specification:

$$ s_{it} = \phi'_0 + \phi'_1 x_{it}^P + \phi'_2 \delta_{it} + \Theta' Z_{it} + e'_{it}. $$

Based on earlier derivations, this equation can be estimated using $E_{i,t}(x_{i,t+1})$ to measure $x_{it}^P$, and $x_{it} - E_{i,t}(x_{i,t+1})$ to measure $\delta_{it}$. Following the same logic for moving from equation (10) to (11), we estimate a version of (13) in which incomes ($x_{it}$) are replaced by relative income ranks ($r_{i,t}$). Since all measures are available for both survey waves, this equation can be estimated using pooled data from the two survey waves.

The relationship between the estimated $\hat{\phi}$ from equation (12) and the estimated $\hat{\phi}'_1$ and $\hat{\phi}'_2$ from equation (13) can be expressed as $\hat{\phi} = \omega_c \hat{\phi}'_1 + (1 - \omega_c) \hat{\phi}'_2$, where $\omega_c = \frac{\sigma_p + \sigma_p \sigma_x}{\sigma_x}$ in

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9 The wealth variables include log of housing value per capita, log of livestock value per capita, and a set of dummies for whether the household owns the consumer durables (large furniture, bicycler, motorbike, electric battery vehicle, radio/recorder, black and white TV, color TV, telephone, mobile phone, audiovisual products, refrigerator, air conditioning, gas stove, sewing machine, camera, washing machine, electric/solar water heater, computer, dispenser, microwave, agricultural motor vehicle, and car/truck). Results without controlling for the wealth variables are available upon request.
the absence of control variables (see derivation in Appendix 3). Here, $\sigma_p$ and $\sigma_x$ are the sample variances of $x_{it}^p$ and $x_{it}$, and $\sigma_{p\delta}$ is the sample covariance between $x_{it}^p$ and $\delta_{it}$.

Similarly, equation (14) presents a typical panel estimation equation, and equation (15) decomposes the income change to allow for different effects of transitory and permanent income shocks.

$$\Delta s_{it+1} = \lambda_0 + \lambda \Delta x_{it+1} + \psi \Delta Z_{it+1} + u_{it+1}, \quad (14)$$
$$\Delta s_{it+1} = \lambda_0' + \lambda_1' \eta_{it+1} + \lambda_2' (\delta_{it+1} - \delta_{it}) + \psi' \Delta Z_{it+1} + u_{it+1}', \quad (15)$$

where $\Delta x_{it+1}$ is the change in income, which from equations (4) and (5) can be modeled as $\Delta x_{it+1} = \delta_{it+1} - \delta_{it} + \eta_{it+1}$. To empirically estimate equations (14) and (15), we again replace income ($x_{it}$) with relative income rank ($r_{it}$) throughout and use the measures for permanent and transitory income shocks defined by equations (8) and (9). Note that the decomposition equation (15) is now very similar to equation (11) derived from the theoretical model, except that the transitory income term is the difference in transitory shocks $\delta_{it+1} - \delta_{it}$ rather than just $\delta_{it+1}$.

We have $\hat{\lambda} = \omega_p \hat{\lambda}'_1 + (1 - \omega_p) \hat{\lambda}'_2$, where $\omega_p = \frac{\sigma_{\eta} + \sigma_{\eta \delta}}{\sigma_{\eta \delta}}$ in the absence of control variables, and $\hat{\lambda}, \hat{\lambda}'_1, \hat{\lambda}'_2, \hat{\psi},$ and $\hat{\psi}'$ are ordinary least square estimators of regression equations (14) and (15). Here, $\hat{\sigma}_\eta$ and $\hat{\sigma}_{x}$ are the sample variances of $\eta_{it}$ and $\Delta x_{it}$, and $\hat{\sigma}_{\eta \delta}$ is the sample covariance between $\eta_{it}$ and $\Delta \delta_{it}$.

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10 Adding control variables $Z$ slightly complicates the formulas for calculating $\omega_c$ and $\omega_p$, requiring them to account for possible changes in the coefficients on the controls across different specifications. The adjusted formulas are $\omega_c = \frac{\sigma_{\eta} + \sigma_{\eta \delta}}{\sigma_x} + \frac{(\hat{\psi} - \hat{\psi})_1}{\hat{\phi}_1 - \hat{\phi}_2}$ and $\omega_p = \frac{\sigma_{\eta} + \sigma_{\eta \delta}}{\sigma_{\Delta X}} + \frac{(\hat{\psi} - \hat{\psi})_1}{\hat{\lambda}_1 - \hat{\lambda}_2}$, where $\hat{\psi}$ and $\hat{\tau}$ are the ordinary least squares coefficients from the regressions $Z_{it} = \gamma_0 + \gamma^\prime x_{it} + \epsilon_{it}^\prime$ and $\Delta Z_{it} = \tau_0 + \tau \Delta x_{it} + \epsilon_{it}'$. 

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Assuming \{\eta_t\} and \{\delta_t\} are mutually independent over time, we have \( \frac{\partial x_t^P}{\partial \eta_t} = 1 \) and \( \frac{\partial \Delta \delta_t}{\partial \delta_t} = 1 \). Since \( V_{t-1} \) is independent of \( \eta_t \) according to the rational expectations hypothesis, \( \frac{\partial \Delta v_t}{\partial \eta_t} = \frac{\partial v_t}{\partial \eta_t} = \frac{\partial x_t^P}{\partial x_t^P} \frac{\partial \Delta x_t^P}{\partial \eta_t} \). That is, the marginal effect of lifetime income on well-being is the same as the effect of permanent income shocks on the change in well-being, or \( \phi'_1 = \lambda'_1 \). Similarly, we have \( \phi'_2 = \lambda'_2 \). As derived above, \( \phi_1 \) and \( \lambda_1 \) can be interpreted as the weighted average of the effects of permanent and transitory income shocks. The marginal effect of a permanent income shock on well-being is greater than that of a transitory income shock. We posit that \( \omega_c > \omega_p \), or that the relationship between income and SWB found in cross-sectional regression is stronger than that in panel regression, that is \( \phi > \lambda \).\(^{12}\)

4. Data

The data used in this study are from the Chinese Rural Residents Living and Health Survey, a longitudinal household survey of a stratified random sample of rural households in China. The survey was conducted in 2006 and 2009 in 64 villages in four counties, two in Shandong Province in Eastern China, one in Sichuan Province in Western China, and one in Anhui Province in Central China. Four townships were randomly selected in each county, four villages were randomly selected in each town, and households were randomly sampled in each village. Overall, 1810 households were surveyed in 2006 and 1499 households (83%) were successfully re-interviewed in 2009.

\(^{11}\) To make this more clear, we rewrite the lifetime component of income at time \( t \) as \( x_t^L = \eta_t + \eta_{t-1} + \cdots + \eta_1 + \omega_0, \eta_t \) is a permanent income shock at time \( t \). It is a component of lifetime income at time \( t \), in the sense that it is a component of income at time \( t \), as well as of income in all future periods. Similarly, \( \eta_1, \cdots, \eta_{t-1} \) are also components of lifetime income at time \( t \). \( \omega_0 \) is an initial lifetime component, which is assumed to be determined by observable characteristics \( X \) in the form \( \omega_0 = \Gamma X \). We have \( \frac{\partial x_t^L}{\partial \eta_t} = 1 \), when \( \{\eta_t\} \) is independent over time.

\(^{12}\) We provide more explanation on the hypothesis \( \omega_c > \omega_p \) in Section 5.
Only individuals aged 18 to 60 who live in the household or whose official residential registration is in the household were eligible to answer the questions on subjective relative income. The total number of such individuals in the 1499 households surveyed in both years was 3232, among which 983 people actually answered the questions on subjective relative income in both years. Many household members migrated or were not at home in at least one of the survey years. Another 23 respondents had incomplete data on the global life satisfaction questions and/or other control variables. Thus, our sample for analysis is comprised of 960 individuals living in 780 households who have complete data for both years. We use the inverse probability weighting (IPW) method proposed by Wooldridge (2002) to adjust for bias associated with selection and attrition of the sample.

We use global life satisfaction as our measure of SWB (defined as expected lifetime utility, or the sum of current and future discounted utility). In the survey, people are asked “Generally speaking, are you satisfied with your life?” There are five possible answers: 1 very dissatisfied; 2 dissatisfied; 3 just so so; 4 satisfied; and 5 very satisfied. In the literature,

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13 Many household members were not at home when the survey was being conducted. Among the 2249 individuals who were eligible but didn’t answer the questions on subjective relative income in one of the years, 1011 (45%) were migrants and not living at home at the time of the survey, while others were at school or at their workplace at the time of the survey.

14 Among the 780 households, 601 households have one observation in our panel analysis, 178 households have 2 observations, and 1 household has 3 observations. In all regressions standard errors are clustered by household to account for possible correlation in SWB among household members.

15 We first estimate a probit model for whether the respondent answered the questions on global life satisfaction and subjective income positions among eligible household members in year 2006, and then estimate another probit model for the attrition of the selected sample. The predicted probabilities of selection are multiplied by the probability of attrition. Then the inverse of the probabilities are used as weights in the analyses. In both probit regressions, we control for age, age squared, gender, dummies for marital status, education categories, household size, number of migrants in the household, share of family members who are aged less than 18, older than 60, male, married, and have different levels of education (primary school, middle school, high/vocational school, college or above), log of household income per capita, wealth variables, and village dummies.

16 Table A1 reports results tests of the mean differences in individual characteristics between the total sample and the analysis sample (which is smaller due to missing data and attrition). The results show that the analysis sample on average are older, less likely to be men, more likely to be married, and less educated than the total sample. By using inverse probability weights, the differences are reduce quite a lot for age, gender, marital status, and low education categories. The t tests suggest that the difference in means are statistically significant in all of the individual characteristics when the analysis sample is unadjusted, but after adjustment using inverse probability weights, the two samples are not different in means for half of these variables at the 10% significance level.

17 In the survey, the question of global life satisfaction was asked at the beginning of the third part in the questionnaire following general household questions and the basic demographic questions of household
Global life satisfaction or happiness is widely used to measure utility (Clark et al., 2008). Becker and Rayo (2008) have raised the concern that happiness may be just one argument in the utility function, so that utility could decrease as happiness increases if there was a sufficient reduction in the consumption of other commodities. However, we consider this to be less of a problem for global life satisfaction than for hedonic measures of well-being, such as experienced well-being, or domain specific life satisfaction, such as job satisfaction. Global life satisfaction covers a much wider time and domain span than other measures (Easterlin, 2006). Benjamin et al. (2014) find that people are willing to sacrifice many other aspects of utility for a small increase in global life satisfaction, suggesting that it is capturing overall individual welfare. Life satisfaction also has been found to increase with changing expectations of future material circumstances controlling for current expenditures (Senik, 2008; Frijters et al., 2012), which supports our defining SWB to reflect both current and future utility. For these reasons, we believe global life satisfaction is an appropriate measure for expected lifetime utility.

As noted above, we construct two sets of income measurements from the survey. One is objective income, measured by household income per capita. In addition, we constructed the relative income position in the village according to the relative rank of household income per capita among sampled households in each village in each year. The other is subjective members. Therefore, the answers to the global life satisfaction are unlikely to be influenced by the order of questions, as criticized by Kahneman et al. (2006) which they attribute to “focusing illusion”. Kahneman and Deaton (2010) find that greater income is associated with higher life satisfaction, but not hedonic well-being beyond a certain threshold. It is worth mentioning that the puzzling income-SWB association in individual cross-sectional and panel analysis is for life satisfaction, not for hedonic measures of well-being. The calculated household income is the total income of the household in the one year prior to the survey. It is the sum of income from various sources, including revenue from agriculture, forestry, animal husbandry, fisheries and other businesses, wages, asset revenue, transfers, remittances, and others. We exclude migrants who are away for most of the year when calculating per capita income. Based on the survey design, households were randomly selected in each village. Replacement of households because of attrition in the second survey was based on a rule of economic similarity. Hence the relative income position of sampled households in each village should be an unbiased measure of their income position in the village. That is, the constructed income rank and the self-reported income rank in the village share the same comparison group. To test the randomness of sampling, we calculated the Spearman’s rank correlation coefficient for constructed income rank and self-reported income rank in the village, which is 0.2459. The
income, from self-reports of the household’s relative economic position in the village at the time of the survey, as well as the expected income position in the village three years later (see Appendix 4 for specific wording of the questions). In the analysis, the expected income is measured as the expectation of income position in the village in year 2009 which is reported in the baseline year 2006. There may exist reporting biases in answering questions about expectations for the future. For instance, optimistic (pessimistic) people may be happier (sadder) and also predict higher (lower) relative incomes in the future. To control for such outlook bias (Mangyo and Park, 2011), we adjust the expectation of future income position in the village by a measure of individual-specific outlook bias, which we estimate as the difference between actual income rank (constructed by the rank of household income per capita in the village) and self-reported income rank in the village in the baseline year 2006. The results are not sensitive to this adjustment.

The unexpected income shock is measured as the difference between realized and expected income position in the village in year 2009. We further divide the unexpected income shock into permanent and transitory income shocks. Permanent income shocks are measured as the difference between expected future income position in the village reported in year 2009 and in 2006. Transitory income shocks are measured as unexpected income shocks minus permanent income shocks.21

Table 1 reports descriptive statistics for the variables used in the analysis among the balanced sample. The means and standard deviations are adjusted by IPW. As indicated above, the measure of global life satisfaction ranges from 1 to 5; the higher the value, the more satisfied is the individual. The average global life satisfaction was 3.81 in 2006 and

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21 The decomposition of expected income requires at least three years of data on income in current period and expatiation of income in future period.

21 We are not able to identify either expected permanent income change or expected transitory income change by using two years of data available. It can be shown clearly from the equation $E_t(x_{t+1}) = x_t - \delta_t = x_{t-1} - \delta_{t-1} + \eta_t$.
declined slightly in 2009. Comparing the two sets of income measures, we find that expectations of future income position are on average greater than current income position. As expected, the average age of the sample increased by three, while gender, marital status, and education were generally unchanged between the two years. Household size also on average remains unchanged, while the number of migrants in the household decreased. The average household income per capita increased by 26% in real terms over the 3-year time period (using provincial rural CPI to correct for inflation). These simple statistics suggest that, on average, the increase in income was not associated with an increase in SWB over time. We dig deeper into the relationship between income and SWB below.

5. Results

We first replicate the cross-sectional and panel regressions of income and SWB used in previous studies:

\[
s_{it} = \phi_0 + \phi x_{it} + \Theta Z_{it} + e_{it}, \text{ and}
\]

\[
s_{it} = \phi_0 + \phi x_{it} + \Theta Z_{it} + i + u_{it}.
\]

Following the literature, the control variables include age, age square, gender, marital status (married or not), education (five categories), year dummy.\textsuperscript{22} Since migration is popular in the survey areas and it is found to affect SWB of left behind independently (Lee and Park, 2010), we also control for variables of household composition, including household size, number of migrants in the household, share of household members aged younger than 18, and share of household members aged older than 60. Results of the above two estimation equations are reported in Table 2. The first two columns report the results of the pooled OLS estimation, which includes the main covariate \textit{log of household income per capita} and controls for individual and household characteristics. As shown, SWB increases significantly with income.

\textsuperscript{22} Previous study found that education has independent role on SWB other than through income (Blanchflower and Oswald, 2004).
More specifically, the coefficient of 0.154 implies that a 10 percent increase in income is associated with an increase in SWB of 0.0154 (or 0.018 standard deviations measured in the baseline year). The results in the last two columns control for individual fixed effects. The coefficient on log income per capita decreases substantially to 0.074 and is no longer statistically significantly different from zero. The results are consistent with previous findings of other studies that the relationship between income and SWB is positive and significant in cross-sectional analysis, but the association disappears or is much weaker in panel analysis (Ferrer-i-Carbonell and Frijters, 2004; Winkelmann et al., 1998). The coefficients of other covariates are generally consistent with expectations. Life satisfaction has a U-shaped relationship with age in cross-section. Females and more educated persons express greater life satisfaction. Those living in households with more old people are less satisfied. Conditioning on other factors, life satisfaction declines from 2006 to 2009.

The results of testing for different effects of unexpected permanent and transitory income shocks on changes in SWB as specified in equation (11) are reported in Table 3. The control variables are the same as those listed in Table 2 as well as wealth variables. A lagged dependent variable is also included to account for state dependence due to mean reversion given the fixed scale for reporting SWB and to avoid bias from reverse causality if SWB affects later earnings (De Neve and Oswald, 2012). Results reported in columns (1) and (2) including each income measure separately suggest that permanent income shocks have positive and significant effects on SWB, while the effect of transitory income shocks are much smaller and not significantly different from zero. The results including both income measures reported in column (3) confirm this difference. A permanent income shock that increases the relative income rank in the village by one decile (10 percentage points)

\[ 23 \]

Moreover, as found in De Neve and Oswald (2012), SWB may affect income persistently later in life and so have a greater impact on permanent income than transitory income. To control for this potential reverse causality bias, in all regressions in which we include permanent and transitory income shock as regressors, we check the robustness to controlling for lagged SWB. We find that all results are robust to the inclusion of a lagged depended variable; these results are available upon request.
increases subjective well-being by 0.039, compared to just 0.013 (and not significant) for a transitory shock. In addition, the p value of the Wald test leads us to reject the hypothesis that $\beta_1' \leq \beta_2'$ at the 5% significance level.\footnote{Sacks et al. (2010) find that permanent income (instrumented by education) has a strong impact on SWB using Gallup data when pooling individuals from many countries. Knabe and Ratzel (2011) also find greater effects of permanent income (measured as average income over all years for persons in the panel) than transitory income on SWB, using the German Socio-Economic Panel data. But they didn’t distinguish between the different effects of unexpected permanent and transitory income shocks on SWB.}

Table 4 presents the results when we decompose income into its component parts when estimating conventional cross-sectional and panel specifications, which provides convincing evidence in support of our explanation for the differences in the relationship between SWB and income in cross-sectional and panel analysis. Columns (1) and (2) report the cross-sectional estimation results for equations (12) and (13), while columns (3) and (4) report the panel estimation results for equations (14) and (15). Relative income variables are used throughout. Village-year fixed effects (village fixed effects) are included in the pooled cross-sectional (panel) estimations to account for year specific village-level unobservables. We included the same control variables listed in Table 2 in the cross-sectional analysis. For the panel analysis, we included the same control variables as in Table 3, with the exception of changes in wealth variables. As before, we find that the cross-sectional results reveal a stronger relationship between SWB income than the panel results (comparing column (1) and (3)). A formal Wald test on $\phi = \lambda$ leads us to reject the null hypothesis at the 5% significant level. However, when we distinguish between permanent and transitory income, the estimated effects of each component are much more similar comparing the cross-sectional and panel results. The coefficients on lifetime income and permanent income shocks are similar in magnitude (columns (2) and (4)), as are the coefficients on transitory income shocks and on changes in transitory income shocks. Wald tests for $\phi_1' = \lambda_1'$ and $\phi_2' = \lambda_2'$ find that we cannot reject the null hypotheses at the 10% significance level. The key difference between the cross-sectional and panel analysis thus must be that the relative weight of
permanent income in total income variation is greater in the cross-sectional regression. We further test the hypotheses that $\phi_1' \leq \phi_2'$ and $\lambda_1' \leq \lambda_2'$ using within equation comparisons of coefficients. The $p$ value of the Wald tests are 0.003 and 0.039 separately, leading us to reject these hypotheses at the 5% significant level.

Table 5 reports the calibration of the parameters $\theta_x$, $\theta_p$, $\theta_{\rho \delta}$, $\theta_{\Delta x}$, $\theta_{\eta}$, $\theta_{\eta \Delta \delta}$ and $\theta_{\Delta \delta}$ from the data. The variance of the transitory income shock ($\theta_{\delta}$), permanent income shock ($\theta_{\eta}$), and lifetime income components ($\theta_p$) are 7.81, 5.83 and 10.57 separately. Calculation of $\omega_c$ and $\omega_p$ from the equations $\omega_c = \frac{\theta_p + \theta_{\rho \delta}}{\theta_x}$ and $\omega_p = \frac{\theta_{\eta} + \theta_{\eta \Delta \delta}}{\theta_{\Delta x}}$ reveal that $\omega_c = 0.680$ and $\omega_p = 0.107$ (column 1 in Panel B). This finding provides strong support for our contention that cross-sectional regressions put a significantly greater weight on variation in the permanent component of income than panel regressions. We do not expect the adjustments accounting for possible changes in the coefficients on the controls to strongly influence the gap between $\omega_c$ and $\omega_p$ since we do not have any reason to expect the coefficients on the controls to vary differently across specifications in the cross-sectional and panel regressions. Using the adjusted formulas, we find that $\omega_c = 0.675$ and $\omega_p = 0.116$ (column 2), which are both close to the unadjusted estimates. The conclusion that $\omega_c > \omega_p$ is confirmed.

6. Extensions

Credit Constraints

Thus far we have assumed perfect credit markets whereby individuals can borrow and save freely at an exogenous interest rate. In reality, this is unlikely to hold true for many households even in developed countries but especially in developing countries. Empirical studies in developing countries have found different response patterns of consumption with respect to positive and negative transitory income shocks, and for low-wealth and high-
wealth households (Morduch, 1990; Fafchamps and Lund, 2003; Rosenzweig and Wolpin, 1993; Fafchamps et al., 1998; Cameron and Worswick, 2003; Rosenzweig, 2001; Meng, 2003). We investigate the role of liquidity constraints by distinguishing positive and negative transitory income shocks and test for their effects on the well-being of households with low wealth and high wealth.

We extend the benchmark model by investigating how well-being is affected by permanent and transitory income shocks when households are credit constrained.\(^{25}\) Now, households are subject to an additional liquidity constraint \((1 + r)w_t + x_t - c_t \geq 0\). We focus on cases when \(E_{t-1}[(1 + r)w_t + x_t - c_t] \geq 0\), or equivalently \(E_{t-1}(w_{t+1}) \geq 0\). In words, based on information available at time \(t - 1\), the liquidity constraint is not binding. Adjustment in consumption can be expressed as a function of the permanent and transitory income shocks,

\[
c_t - c_{t-1} = \mu_1 \eta_t + \mu_2 \delta_t.
\]

As derived earlier, the policy function in the case of perfect credit markets is \(\mu_1 = 1\) and \(\mu_2 = \frac{r}{1 + r}\). Since optimal consumption adjusts one to one with permanent income shocks, the liquidity constraint \((1 + r)w_t + x_t - c_t \geq 0\) is never binding. Therefore the first best solution can be achieved, and \(\mu_1 = 1\) also holds for permanent income shocks even in the case of imperfect credit markets.

For transitory income shocks, we distinguish between positive and negative transitory income shocks. If the credit constraint is not initially binding, in the case of positive transitory income shocks the first best solution can always be achieved, and \(\mu_2 = \frac{r}{1 + r}\) still holds. In the case of negative transitory income shocks, the first best solution can not always be achieved, since the liquidity constraint \((1 + r)w_t + x_t - c_t \geq 0\) may be binding. For

\(^{25}\) Studies found response of consumption to a transitory income shocks is more sensitive than predicted in the standard model. For instance, Gertler and Gruber (2002) found illness is associated with significant fall in consumption in Indonesia. Cameron and Worswick (2003) found the role of saving is incomplete in allowing households to smooth consumption in the face of crop losses.
example, when $x_t$ decreases by amount $|\delta_t|$ because of a negative transitory shock, the optimal adjustment with perfect credit markets is to decrease consumption by the amount $r|\delta_t|/(1 + r)$ for each subsequent period. However, if the household cannot self-finance the negative transitory shock and the liquidity constraint is binding, then $\mu_2 > \frac{r}{1+r}$. One extreme case is when $E_{t-1}(w_{t+1}) = 0$, in which case $c_t$ needs to adjust one to one with the negative income shock ($\mu_2 = 1$). The effects on consumption of a negative transitory income shock thus can be summarized as follows:

$$
\begin{cases}
\mu_2 = 1, \; \delta_t < 0 \text{ and } E_{t-1}(w_{t+1}) = 0 \\
\frac{r}{1+r} < \mu_2 < 1, \; \delta_t < 0 \text{ and } 0 < E_{t-1}(w_{t+1}) < \frac{|\delta_t|}{1+r} \\
\mu_2 = \frac{r}{1+r}, \; \delta_t < 0 \text{ and } E_{t-1}(w_{t+1}) \geq \frac{|\delta_t|}{1+r}
\end{cases}
$$

In the extreme case where $\delta_t < 0$ and $E_{t-1}(w_{t+1}) = 0$, the first best consumption choice is not achievable, implying that welfare is worse compared with that achieved in the model with perfect credit markets. The credit constraint introduces additional variation in consumption, and leads to a welfare loss equal to $b\beta\delta_t^2/2$ (see Appendix 5 for derivation). The marginal effect of a negative transitory income shock on well-being is $\frac{r}{1+r} \frac{u'(c^*_t)}{1-\beta} + b\beta|\delta_t|$, where $c^*_t$ is the first best choice of consumption with perfect credit markets. The effect is greater than the marginal effect of the positive transitory income shock on well-being, but is smaller than the marginal effect of the permanent income shock on well-being when $|\delta_t| < \frac{u'(c^*_t)}{b(1-\beta)}$ (and larger when the inequality sign is reversed).

Since the welfare loss is the greatest in the extreme case, it provides an upper bound for the marginal effect of a negative transitory income shocks on well-being. For households that are partially self-financing, the predictions are similar but the effects may be smaller in magnitude.

To sum up, when the credit market is imperfect, theoretical predictions about the adjustment of consumption to income shocks differs from that of the benchmark model when
households are unable to finance the same level of consumption as that predicted by a model with perfect capital markets. The welfare implications are complicated. When the credit constraint binds, the marginal effect on welfare of a negative transitory income shock can either be greater or smaller than that of a permanent income shock, depending on the magnitude of the negative transitory income shocks and households’ capability to self-finance. The marginal effect on welfare of a positive transitory income shock is always smaller than that of a permanent income shock.

The results of empirical tests of these predictions are reported in Table 6. Regression results reported in Column (1) are based on a model that allows for asymmetric effects of positive and negative income shocks:

\[ \Delta s_{i,t+1} = \beta_0 + \beta_1 \eta_{t+1} + \beta_{2,neg} \delta_{t+1} \cdot 1(\delta_{t+1} < 0) + \beta_{2,pos} \delta_{t+1} \cdot 1(\delta_{t+1} > 0) + \gamma_j + \psi Z_{i,t+1} + \xi_{i,t+1} \]

where \( \eta_{t+1} = [E_{i,t+1}(r_{i,t+2}) - E_{i,t}(r_{i,t+1})] \), \( \delta_{t+1} = [r_{i,t+1} - E_{i,t+1}(r_{i,t+2})] \), and \( 1(\cdot) \) is an index function. The effect of permanent income shocks on SWB is nearly the same as that in Table 3. Interestingly, we find that the marginal effect on SWB is positive and significantly different from zero for negative transitory income shocks. That is, people are significantly worse off even when the negative income shock is transitory. This suggests that on average people are unable to efficiently smooth consumption when they face negative transitory income shocks. The results also indicate there is no significant change in SWB for positive transitory income shocks. Wald tests find that the coefficient on the permanent income shock is significantly greater than that on the positive transitory income shock; while it is not significantly different from that of a negative transitory income shock.\(^{26}\)

Studies have found that assets, such as livestock, can serve as a buffer stock in rural households of developing countries (Rosenzweig and Wolpin, 1993; Fafchamps et al., 1998).\(^{26}\)

\(^{26}\)De Neve et al. (2014) found that recessions have a greater impact on individual happiness than periods of growth, which they attribute to macroeconomic loss aversion.
Moreover, people with greater wealth are more likely to have access to credit markets if assets can be used as collateral (Jalan and Ravallion, 1999). We use assets as a proxy for the likelihood of households being liquidity constrained and investigate the welfare implication of income shocks for subsamples with high and low assets.\textsuperscript{27} As shown in the regression results reported in Column (2) of Table 6, for individuals living in households with low assets, the marginal welfare impact of a negative transitory income shock is 0.045, which is significantly different from zero. The interaction term between the dummy for high assets and the negative transitory income shock is -0.055 and significantly different from zero. The results suggest that for wealthy individuals the marginal effect of negative transitory income shock is close to zero. It justifies the theoretical prediction that transitory income shocks only have significant impacts on SWB when individuals face negative income shocks with limited credit.

\textit{Finite Time Horizon}

In the benchmark model, we assume the time horizon is infinite. Now we loosen the assumption by assuming the head of the household dies at age $A$ leaving no bequest. In this case,

$$c_t - c_{t-1} = \eta_t + \tilde{y}_t \delta_t,$$

where \( \tilde{y} = \frac{r}{1+r} [1 - (\frac{1}{1+r})^{A-a+1}]^{-1} \), and $a$ is the age of the household head at time $t$. Since $\tilde{y}$ increases with $a$, one implication of the finite time horizon model is that the response of consumption to transitory income shock is greater for household with older head. This relationship maps to the impact on well-being. More specifically, we have $\partial(\Delta v_t)/\partial \eta_t = u'(c_t)g(\beta; a)$ and $\partial(\Delta v_t)/\partial \delta_t = \tilde{y} u'(c_t)g(\beta; a)$, where $g(\beta; a) = (1 - \beta^{A-a+1})(1 - \beta)^{-1}$.

\textsuperscript{27} We construct a wealth index for each household by performing a principle-component factor analysis among a set of variables that measure household’s wealth. See footnote 9 for more details.
and $\bar{p} \leq 1$ (equality holds when $a=A$). Table 7 reports empirical results on testing the predictions among household with head of different age groups.

We divide the sample into two subgroups by the age of household head. For those in households with heads aged between 21 and 45 years old, we find the marginal effect of transitory income shocks is not significantly different from zero. The effect of a permanent income shock is positive, but not statistically significantly either. In contrast, for individuals in households with heads who are older, the marginal effect of a transitory income shock is positive and significantly different from zero. This finding confirms the theoretical prediction that older people are more affected by transitory income shocks given their shorter time horizon for smoothing consumption. The marginal effect of a permanent income shock is also significantly greater than zero. The Wald tests suggest that for both groups of people, the marginal effect of a permanent income shock on SWB is greater than that of a transitory income shock.

7. Robustness

Tests of Rational Expectations

One implication of the rational expectation model is that the expected income contains information on actually realized income. We verify this by estimating following equation

$$x_{i,j,t+1} = \sum_j \beta_j E_{it}(r_{ij,t+1}) + v + \varepsilon_{i\nu,t+1},$$

where $x_{i,j,t+1}$ is the log income per capita of household $i$ in village $j$ at time $t + 1$, and $r_{ij,t+1}$ is the relative income of household $i$ in the village. The regression includes a village fixed effect and village-specific slope to account for heterogeneity in income variance across villages. The predicted values from the regression can reasonably be interpreted as the expected value of absolute income next period. We also replace the expected relative income in the above regression by constructed relative income, self-reported relative income and adjust-expected
relative income. The predicted and actual values of log income per capita in year 2009 are plotted in Figure A1. As a benchmark, Panel A shows that the predicted values from constructed relative income are in line with actual absolute incomes. The R-squared of the estimation is almost 1, suggesting the constructed relative income can recover almost all of the information on absolute income using the above estimation model. Panel B shows the plot of predictions from self-reported relative income. The scope of the predicted values is narrower than those of constructed relative income, reflecting the fact that most respondents report their relative income position around the middle of the scale. But the scatter plot shows most of the points are around the 45 degree line, especially observations with greater weight (indicated by markers with bigger size). Panel C shows the plot of predicted values from the expected relative income and the actual log income per capita. It does as good a job as self-reported relative income in terms of R-squared, verifying the role of expectations in predicting future income. The explained variance by the model increases when the expected relative income is adjusted for outlook bias, measured as the difference between constructed relative income and self-reported relative income in the baseline year 2006.

**Measurement Error**

One common explanation for the weaker correlation between SWB and income in panel analysis is that the signal to noise ratio is lower in panel regressions than in cross-sectional regressions (Layard et al., 2008). The first difference eliminates most of the signal in measured income, while errors dominate the variation used for identification. We do not believe that the measurement error is likely to explain our findings. First of all, in our main analysis, income is measured in relative form and in deciles, so the errors in the measurement

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28 In addition to the reporting scale, other reasons for imperfect prediction include the outlook bias of self-reported values, and the log household income per capita may be imperfect measures of individual income.

29 The Spearman’s rank correlation coefficient for expected and self-reported relative income of year 2009 is 0.3078. The null hypothesis of independency of the two variables is rejected on significant level 1%.
will be less serious than for self-reported income in monetary units. Secondly, if error dominates the signal in first differences, we would expect to find no significant correlation between SWB and permanent income shocks. However, we actually find that permanent income shocks significantly increase SWB. Lastly, we use the predicted values of the log of household income per capita from the self-reported relative income in the village as an instrument for the actual values of the log of household income per capita and re-estimated the regressions in Table 2 (assuming the measurement error is classical). The results are reported in Table A2. The first four columns show the reduced form regressions results, while the last four columns show the IV regression results. The $F$ statistics of the weak instruments test for cross-section and panel analysis are 450.01 and 116.48 separately. For both IV and reduced form estimations, the relationship between income and SWB are consistently weaker in the panel than in the cross-section analysis, even though the coefficients of the IV estimations are greater than those in Table 2 for both cross-section and panel analysis. To sum up, measurement error in income appears unlikely to explain the different correlation between SWB and income using cross-sectional and panel specifications.

**Alternative Explanations**

We consider the possibility that other omitted variables can explain the differences found in cross-sectional versus panel studies. First, we examine the possibility that health could play a key role by directly controlling for self-reported health status in the same regressions reported in Table 2.\(^{30}\) The new results are reported in Table A3. Columns 1 and 2 show that after controlling for health the coefficient on income in the cross-sectional regression decreases by 19% (from 0.154 to 0.125), but it is still significantly greater than

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\(^{30}\) Our measure of self-reported health status is an ordinal scale with five possible values: 1. very poor, 2. poor, 3. fair, 4. good, 5. very good.
zero. In addition, even after controlling for health, we continue to observe a weaker association of income and SWB in panel analysis than in cross-sectional analysis.

As discussed in the introduction, another possible alternative explanation is relative income as aforementioned. However, controlling for the self-reported income rank in the village in the regressions reported in Table 2 does not affect our conclusions. Columns 5 and 6 in Table A3 show that even though self-reported income rank in the village is positively and significantly correlated with global life satisfaction, greater income continues to be associated with a significant increase in SWB apart from its indirect effect through relative income. Moreover, controlling for self-reported income rank doesn’t explain the puzzle. The last two columns show the association between income and SWB in panel analysis are still not significantly different from zero.

It is impossible to completely rule out the possibility that other omitted factors could explain the stronger association of income and SWB in cross-sectional versus panel analysis. Nonetheless, given that income has been clearly shown to significantly influence SWB, we believe that our theoretically well-grounded explanation is likely to play some role in explaining the inconsistency.

8. Conclusion

In this study, we propose a new explanation for the inconsistent relationship between income and SWB found in previous cross-sectional and panel studies. We argue that income only significantly impacts well-being if it reflects differences in permanent income. Our benchmark model of welfare analysis based on the RE-PIH suggests the marginal welfare effect of a permanent income shock is greater than that of a transitory income shock. This prediction is confirmed by our analysis of panel data from China. Thus, the different relationships found in the literature, as well as in our study, reflect differences in the type of
variation in income used for identification in cross-sectional and panel analysis. The share of the variation in total income accounted for by the lifetime component of income in cross-sectional comparisons is found to be greater than the share of the variation in income changes accounted for by unexpected permanent income shocks in panel specifications. Since the marginal welfare impact of the permanent income shock is greater than that of the transitory income shock, we expect a much more significant correlation between income and SWB in cross-section analysis than in panel analysis. Our empirical results support these predictions.
References


Lee, Leng, and Albert Park. 2010. “Parental Migration and Child Development in China,” mimeo, Hong Kong University of Science and Technology.


Appendix 1

We can generate a similar prediction for a general utility function if we define subjective well-being to be expected lifetime utility (the sum of current and future discounted utility). Taking a Taylor expansion of \( u(c_{t+s}) \) around \( c_t \), there exists some \( c_s \) lying between \( c_{t+s} \) and \( c_t \) such that

\[
u(c_{t+s}) = u(c_t) + u'(c_t)(c_{t+s} - c_t) + \frac{u''(c_s)}{2}(c_{t+s} - c_t)^2. \tag{A1}\]

By taking expectations at time \( t \) of both sides of equation (A1), we get

\[
E_t[u(c_{t+s})] = u(c_t) - \frac{b}{2} \text{Var}_t(c_{t+s}). \tag{31}
\]

Therefore,

\[
V_t = E_t[\sum_{s=0}^{\infty} \beta^s u(c_{t+s})] = \frac{1}{1-\beta} u(c_t) - \frac{b}{2} \sum_{s=1}^{\infty} \beta^s \text{Var}_t(c_{t+s}).
\]

Taking first differences of both sides yields:

\[
\Delta V_t = \frac{1}{1-\beta} \Delta u(c_t). \tag{A2}
\]

From (A1) and (A2), we get the following:

\[
\Delta V_t = \frac{u'(c_{t-1})}{1-\beta} \Delta c_t - \frac{b}{2(1-\beta)} (\Delta c_t)^2. \tag{A3}
\]

Therefore,

\[
\Delta V_t = \frac{u'(c_{t-1})}{1-\beta} (\eta_t + \frac{r}{1+r} \delta_t) - \frac{b}{2(1-\beta)} (\eta_t + \frac{r}{1+r} \delta_t)^2 \tag{A4}
\]

From equation (A4), we know \( \frac{\partial(\Delta V_t)}{\partial \eta_t} = \frac{u'(c_t)}{1-\beta} \), and \( \frac{\partial(\Delta V_t)}{\partial \delta_t} = \frac{r}{1+r} \frac{u'(c_t)}{1-\beta} \). This suggests that a permanent income shock has a greater effect on well-being than a transitory income shock.

\[31\text{ For quadratic preferences, we have } u''(c_s) = -b, \text{ which is constant. This helps to simplify the expectation of the third term in equation (A1). For a class of more general utility functions with property of constant relative risk aversion (CRRA), this can be approximated by some constant under certain assumption. Details are included in the Appendix 2.}\]
Appendix 2

CRRA Preferences

In the benchmark model, we assume that preferences are quadratic. Here, we consider what happens if preferences exhibit constant relative risk aversion (CRRA), following the method used in Blundell, Low, and Preston (2004) and Blundell, Pistaferri, and Preston (2008).

A.4.1 Approximating the Euler Equation

Consider a utility function $u(c) = \frac{c^{1-\rho}}{1-\rho}$, $0 < \rho < 1$. The Euler equation turns out to be

$$c_t^{\rho} = \beta (1 + r) E_t (c_{t+1}^{\rho}).$$

(A5)

Noting $c_t^{\rho} = e^{-\rho \ln (c_{t+1})}$ and assuming $\beta (1 + r) = 1$, (A5) can be rewritten as

$$e^{-\rho \ln (c_t)} = E_t (e^{-\rho \ln (c_{t+1})}).$$

Take a Taylor expansion of $f(y) = e^{-\rho y}$ around $y_0 = \ln (c_t)$, and evaluate it at $y = \ln (c_{t+1})$. There exists some $\bar{c}$ between $c_t$ and $c_{t+1}$ such that

$$c_t^{\rho} = c_t^{\rho} [1 - \rho (\Delta \ln (c_{t+1})) + \frac{\rho^2}{2} (\frac{\bar{c}}{c_t})^{\rho} (\Delta \ln (c_{t+1}))^2].$$

(A6)

Take expectations of (A6)

$$E_t (c_t^{\rho}) = c_t^{\rho} [1 - \rho E_t (\Delta \ln (c_{t+1})) + \frac{\rho^2}{2} E_t \left( \frac{\bar{c}}{c_t} \right)^{\rho} (\Delta \ln (c_{t+1}))^2].$$

Substituting for $E_t (c_t^{\rho})$ from (A5),

$$E_t (\Delta \ln (c_{t+1})) = \frac{\rho}{2} E_t \left( \frac{\bar{c}}{c_t} \right)^{\rho} (\Delta \ln (c_{t+1}))^2].$$

(A7)

$$\zeta_{t+1} \equiv \ln (c_{t+1}) - E_t (\ln (c_{t+1})).$$

Then,

$$\Delta \ln (c_{t+1}) = \zeta_{t+1} + \frac{\rho}{2} E_t \left( \frac{\bar{c}}{c_t} \right)^{\rho} (\Delta \ln (c_{t+1}))^2].$$

Noting that $E_t (\zeta_{t+1}^2) = E_t [(\Delta \ln (c_{t+1}))^2] - [E_t (\Delta \ln (c_{t+1}))]^2$ and substituting $E_t (\Delta \ln (c_{t+1}))$ from (A7), we get $E_t [(\Delta \ln (c_{t+1}))^2] = O(E_t (\zeta_{t+1}^2))$. As $E_t (\zeta_{t+1}^2) \rightarrow 0$, $(\frac{\bar{c}}{c_t})^{\rho}$ tends to be constant. Therefore,

$$\Delta \ln (c_{t+1}) = \zeta_{t+1} + O(E_t (\zeta_{t+1}^2)).$$

(A8)

Equation (A8) relates consumption growth to its innovations. The order of error in approximation is $O(E_t (\zeta_{t+1}^2))$.

A.4.2 Approximating the Lifetime Budget Constraint

Consider the lifetime budget constraint
\[
\sum_{s=0}^{\infty} \left( \frac{1}{1+r} \right)^{s+1} (c_{t+s}) = w_t + \sum_{s=0}^{\infty} \left( \frac{1}{1+r} \right)^{s+1} (x_{t+s}).
\]

Log-linearizing both sides, we get
\[
\sum_{s=0}^{\infty} \alpha_{s,t,c} \ln(c_{t+s}) - E_t(\ln(c_{t+s})) + O(\| \zeta^t \|^2)
\]
\[
= \pi_t \sum_{s=0}^{\infty} \alpha_{s,t,x} \ln(x_{t+s}) - E_t(\ln(x_{t+s})) + O(\| v^t \|^2),
\]
where \( \pi_t = \frac{\sum_{s=1}^{\infty} \exp[E_t(\ln(x_{t+s}) - (1+s)\ln(1+r))]}{w_t + \sum_{s=0}^{\infty} \exp[E_t(\ln(x_{t+s}) - (1+s)\ln(1+r))]}, \) and \( \alpha_{s,t,x} = \frac{\exp[E_t(\ln(x_{t+s}) - (1+s)\ln(1+r))]}{\sum_{s=1}^{\infty} \exp[E_t(\ln(x_{t+s}) - (1+s)\ln(1+r))]}. \)

Taking expectations of (A9) and then differences between expectations of \( E_{t+1} \) and \( E_t \) gives
\[
\zeta_{t+1} + O(\zeta^2_{t+1}) + O(E_t \zeta^2_{t+1}) = \pi_t (\xi_{t+1} + \alpha_{t,x} \xi_{t+1}) + O(\xi^2_{t+1}) + O(\xi_{t+1}) + O(\delta^2_{t+1}) + O(\delta_{t+1}),
\]
where \( \alpha_{t,x} = \alpha_{1,t,x}. \)

\[\Delta \ln(c_{t+1}) = \pi_t (\delta_{t+1} + \alpha_{t,x} \delta_{t+1}) + O(\xi^2_{t+1}) + O(\xi_{t+1}) + O(\delta^2_{t+1}) + O(\delta_{t+1}). \] (A10)

A.4.3 Approximating the Value Function

Now we consider the theoretical prediction for the effect of income shocks on \( V_t. \)

Taking a Taylor expansion of \( g(y) = \frac{1}{1-p} \exp\left[(1-p)y\right] \) around \( y_0 = \ln(c_t) \) and evaluating it at \( y = \ln(c_{t+s}), \)
\[u(c_{t+s}) = u(c_t)[1 + (1-p)(\ln(c_{t+s}) - \ln(c_t))] + \frac{(1-p)^2}{2} \left( \frac{c_{t+s}}{c_t} \right)^{1-p}(\ln(c_{t+s}) - \ln(c_t))^2\] (A11)

where \( \zeta_{t,x} \) is between \( c_t \) and \( c_{t+s}. \)

Taking expectations at time \( t \) on both sides, we get
\[E_t(u(c_{t+s})) = u(c_t)[1 + (1-p)E_t(\ln(c_{t+s}) - \ln(c_t))] + \frac{(1-p)^2}{2} E_t(\left( \frac{c_{t+s}}{c_t} \right)^{1-p}(\ln(c_{t+s}) - \ln(c_t))^2)]\]

Noting that \( E_t(\ln(c_{t+s}) - \ln(c_t)) \) and \( E_t(\ln(c_{t+s}) - \ln(c_t))^2 \) are independent of \( t, \) substituting \( E_t(u(c_{t+s})) \) from the value function \( V_t = E_t[\sum_{s=0}^{\infty} \beta^s u(c_{t+s})], \) and taking differences, we get
\[\Delta V_{t+1} = \left\{ \frac{1}{1-p} + (1-p) \sum_{s=0}^{\infty} \beta^s E_t(\ln(c_{t+s}) - \ln(c_t)) \right\} \Delta u(c_{t+1})\]
\[+ \frac{(1-p)^2}{2} \sum_{s=0}^{\infty} \beta^s E_t(\left( \frac{c_{t+s}}{c_t} \right)^{1-p}(\ln(c_{t+s}) - \ln(c_t))^2)]\]

From (A11) we can derive the expression for \( \Delta u(c_{t+1}). \) Substituting from (A12), we get
\[
\Delta V_{t+1} = \frac{(1-\rho)u(c_t)}{1-\beta} \Delta \ln(c_{t+1}) + (1 - \rho)u(c_t) \Delta \ln(c_{t+1}) O(\|\xi^t\|^2) \\
+ O[(\Delta \ln(c_{t+1}))^2] + O(\|\xi^t\|^2) O[(\Delta \ln(c_{t+1}))^2]
\]

Substitute \(\Delta \ln(c_{t+1})\) from (A.10),

\[
\Delta V_{t+1} = \frac{(1-\rho)u(c_t)}{1-\beta} \pi_t (e_{t+1} + \alpha_{t,x} \delta_{t+1}) + O(e_{t+1}^2) + O(E_t e_{t+1}^2) + O(\delta_{t+1}^2) + O(E_t \delta_{t+1}^2).
\]

This equation links change in welfare and income innovations. Since \(\alpha_{t,x} < 1\), ignoring the error in the approximation, the model with CRRA preference has the same prediction as that assuming a quadratic utility function. That is, the impact of permanent income shocks on welfare is greater than that of transitory income shocks.
Appendix 3

Consider a regression model \( y = \alpha_0 + \alpha (x_1 + x_2) + e \), the OLS estimator of \( \alpha \) is

\[
\hat{\alpha} = \frac{\text{cov}(y, x_1 + x_2)}{\text{var}(x_1 + x_2)}.
\]

For the other regression model \( y = \alpha'_0 + \alpha'_1 x_1 + \alpha'_2 x_2 + e' \), the OLS estimators are

\[
\hat{\alpha}_1 = \frac{\text{var}(x_2)\text{cov}(y, x_1) - \text{cov}(x_1, x_2)\text{cov}(y, x_2)}{\text{var}(x_1) + \text{var}(x_2) - \text{cov}(x_1, x_2)^2}, \quad \text{and}
\]

\[
\hat{\alpha}_2 = \frac{\text{var}(x_1)\text{cov}(y, x_2) - \text{cov}(x_1, x_2)\text{cov}(y, x_1)}{\text{var}(x_1) + \text{var}(x_2) - \text{cov}(x_1, x_2)^2}.
\]

It can be shown that

\[
\hat{\alpha} = w\hat{\alpha}_1 + (1 - w)\hat{\alpha}_2,
\]

where \( w = \frac{\text{var}(x_1) + \text{cov}(x_1, x_2)}{\text{var}(x_1 + x_2)} \). \( 0 < w < 1 \), if and only if \( \text{var}(x_1) + \text{cov}(x_1, x_2) > 0 \) and \( \text{var}(x_2) + \text{cov}(x_1, x_2) > 0 \).

In a more general case, the two regression models are

\[
y = \beta_0 + \beta (x_1 + x_2) + \gamma Z + u,
\]

\[
y = \beta'_0 + \beta'_1 x_1 + \beta'_2 x_2 + \gamma' Z + u',
\]

where \( Z \) are a vector of other regressors. We have \( \hat{\beta} = \bar{w}\hat{\beta}_1 + (1 - \bar{w})\hat{\beta}_2 \), where \( \bar{w} = w + \frac{(\hat{\gamma}' - \hat{\gamma})\hat{\beta}}{\hat{\beta}_1 - \hat{\beta}_2} \). \( \hat{\beta}_1, \hat{\beta}_2, \hat{\gamma}, \hat{\gamma}' \) are OLS estimators of above regression models. \( \hat{\beta} \) are the estimators of the regression model \( Z = \theta_0 + \theta (x_1 + x_2) + \epsilon \). Under the assumption that \( \frac{(\hat{\gamma}' - \hat{\gamma})\hat{\beta}}{\hat{\beta}_1 - \hat{\beta}_2} = 0 \), we have \( \bar{w} = w = \frac{\text{var}(x_1) + \text{cov}(x_1, x_2)}{\text{var}(x_1 + x_2)} \). By further assuming \( \text{cov}(x_1, x_2) = 0 \), we have \( \bar{w} = \frac{\text{var}(x_1)}{\text{var}(x_1 + x_2)} \).
Appendix 4

Questions on Self-reported Income in the Questionnaires

The self-reported income questions are:

_Imaging a ten-step ladder where on the highest step, the tenth, stand the richest people in your village, and on the bottom, the first step, stand the poorest people in your village,_

(1) On which step of the ten steps are you personally standing currently?
(2) On which step of the ten steps did you personally stand three years ago?
(3) On which step of the ten steps will you personally stand three years later?

(Note: As stated in the training manual for the survey, the interviewers are required to show a picture of a ladder; explain that the top of the ladder represents people with the best economic situation in the village, and the bottom of the ladder represents people with the worst economic situation; then ask the respondents where he or she thinks his/her position is on the ladder.)
Appendix 5

Welfare Implication of Negative Transitory Income Shocks

when the Credit Market is Imperfect

Taking Taylor expansion of \( u(c_{t+s}) \) around \( c_t^* \),

\[
\begin{align*}
    u(c_{t+s}) &= u(c_t^*) + u'(c_t^*)(c_{t+s} - c_t^*) + \frac{u''(c_t^*)}{2} (c_{t+s} - c_t^*)^2,
\end{align*}
\]

where \( c_t^* \) is the optimal consumption choice in benchmark model and \( \hat{c}_t \) lies between \( c_{t+s} \) and \( c_t^* \).

**Case 1: \( E_{t+1}c_{t+1} = 0 \)**

For \( s = 0 \),

\[
\begin{align*}
    u(c_t) &= u(c_t^*) - u'(c_t^*) \left( \frac{\delta_t}{1+r} \right) + \frac{u''(c_t^*)}{2} \left( \frac{\delta_t}{1+r} \right)^2.
\end{align*}
\]

For \( s > 0 \),

\[
E_t[u(c_{t+s})] = u(c_t^*) + u'(c_t^*) \left( \frac{r\delta_t}{1+r} \right) + \frac{u''(c_t^*)}{2} E_t \left( c_{t+s} - E_t c_{t+s} + \frac{r\delta_t}{1+r} \right)^2.
\]

Therefore,

\[
V_t = \frac{1}{1-\beta} u(c_t^*) - \frac{b}{2} \left( \frac{\delta_t}{1+r} \right)^2 - \frac{b}{2} \frac{\beta}{1-\beta} \left( \frac{r\delta_t}{1+r} \right)^2 - \frac{b}{2} \sum_{s=1}^{\infty} \beta^s Var_t(c_{t+s}).
\]

\[
V_t^* - V_t = \frac{b}{2} \left( \frac{\delta_t}{1+r} \right)^2 + \frac{b}{2} \frac{\beta}{1-\beta} \left( \frac{r\delta_t}{1+r} \right)^2 = \frac{b}{2} \beta \delta_t^2,
\]

where \( V_t^* \) the welfare achieved in the benchmark model.

**Case 2: \( 0 < E_{t-1}(w_{t+1}) < |\delta_t|/(1 + r) \) or partially self-finance**

Define \( w = E_{t-1}(w_{t+1}) \)

For \( s = 0 \),

\[
\begin{align*}
    u(c_t) &= u(c_t^*) - u'(c_t^*) \left( \frac{\delta_t}{1+r} - w \right) + \frac{u''(c_t^*)}{2} \left( \frac{\delta_t}{1+r} - w \right)^2.
\end{align*}
\]

For \( s > 0 \),

\[
E_t[u(c_{t+s})] = u(c_t^*) + u'(c_t^*) \left( \frac{r\delta_t}{1+r} - rw \right) + \frac{u''(c_t^*)}{2} E_t \left( c_{t+s} - E_t c_{t+s} + \frac{r\delta_t}{1+r} - rw \right)^2.
\]
Therefore, \( V_t = \frac{1}{1-\beta} u(c^*_t) - \frac{b}{2} \left( \frac{|\delta_t|}{1+r} - w \right)^2 - \frac{b}{2} \frac{\beta}{1-\beta} \left( \frac{|\delta_t|}{1+r} - rw \right)^2 - \frac{b}{2} \sum_{s=1}^{\infty} \beta^s \text{Var}_t(c_{t+s}) \)

\[
V^*_t - V_t = \frac{b}{2} \left( \frac{|\delta_t|}{1+r} - w \right)^2 + \frac{b}{2} \frac{\beta}{1-\beta} \left( \frac{|\delta_t|}{1+r} - rw \right)^2 = b (\beta |\delta_t| - w)^2 / 2 \beta
\]

where \( V^*_t \) the welfare achieved in the benchmark model.
### Table 1: Descriptive Statistics

<table>
<thead>
<tr>
<th>Variables</th>
<th>Year 2006</th>
<th>Year 2009</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean</td>
<td>S. D.</td>
</tr>
<tr>
<td>Global life satisfaction (1-5)</td>
<td>3.81</td>
<td>0.86</td>
</tr>
<tr>
<td>Income (rank in village: 1-10)</td>
<td>5.37</td>
<td>2.70</td>
</tr>
<tr>
<td>Expectation of income three years later (rank in village: 1-10)</td>
<td>6.02</td>
<td>2.21</td>
</tr>
<tr>
<td>Age</td>
<td>36.7</td>
<td>13.7</td>
</tr>
<tr>
<td>Male (dummy)</td>
<td>0.59</td>
<td>0.49</td>
</tr>
<tr>
<td>Married (dummy)</td>
<td>0.71</td>
<td>0.45</td>
</tr>
<tr>
<td>Less than primary school education (dummy)</td>
<td>0.20</td>
<td>0.40</td>
</tr>
<tr>
<td>Primary school education (dummy)</td>
<td>0.25</td>
<td>0.44</td>
</tr>
<tr>
<td>Middle school education (dummy)</td>
<td>0.28</td>
<td>0.45</td>
</tr>
<tr>
<td>High/vocational school education (dummy)</td>
<td>0.24</td>
<td>0.43</td>
</tr>
<tr>
<td>College education or above (dummy)</td>
<td>0.03</td>
<td>0.17</td>
</tr>
<tr>
<td>Household size</td>
<td>3.92</td>
<td>1.38</td>
</tr>
<tr>
<td>Number of migrants in household</td>
<td>0.83</td>
<td>0.99</td>
</tr>
<tr>
<td>Share of family member aged&lt;18</td>
<td>0.19</td>
<td>0.17</td>
</tr>
<tr>
<td>Share of family member aged&gt;60</td>
<td>0.05</td>
<td>0.10</td>
</tr>
<tr>
<td>Log of household income per capita</td>
<td>8.20</td>
<td>0.90</td>
</tr>
</tbody>
</table>

Notes: The sample size is 960 for each year. Means and standard deviations are estimated using inverse probability weights to adjust for sample selection and attrition.
<table>
<thead>
<tr>
<th></th>
<th>Dependent variable: global life satisfaction</th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pooled cross-section</td>
<td>Panel</td>
<td></td>
</tr>
<tr>
<td></td>
<td>coef.</td>
<td>s.e.</td>
<td>coef.</td>
</tr>
<tr>
<td>Log of household income per capita</td>
<td>0.154***</td>
<td>(0.037)</td>
<td>0.074</td>
</tr>
<tr>
<td>Age</td>
<td>-0.056*</td>
<td>(0.031)</td>
<td>n.a.</td>
</tr>
<tr>
<td>(Age/10)^2</td>
<td>0.081**</td>
<td>(0.036)</td>
<td>0.183**</td>
</tr>
<tr>
<td>Male (dummy)</td>
<td>-0.135*</td>
<td>(0.072)</td>
<td>n.a.</td>
</tr>
<tr>
<td>Married (dummy)</td>
<td>0.019</td>
<td>(0.168)</td>
<td>-0.251</td>
</tr>
<tr>
<td>Education=primary school</td>
<td>-0.000</td>
<td>(0.073)</td>
<td>0.037</td>
</tr>
<tr>
<td>Education=middle school</td>
<td>0.138*</td>
<td>(0.076)</td>
<td>0.267*</td>
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<tr>
<td>Education=high/vocational school</td>
<td>0.341**</td>
<td>(0.136)</td>
<td>0.084</td>
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<tr>
<td>Education=college or above</td>
<td>0.348</td>
<td>(0.291)</td>
<td>-0.135</td>
</tr>
<tr>
<td>Household size</td>
<td>0.030</td>
<td>(0.030)</td>
<td>-0.007</td>
</tr>
<tr>
<td>Number of migrants in household</td>
<td>0.011</td>
<td>(0.038)</td>
<td>-0.016</td>
</tr>
<tr>
<td>Share of family member aged&lt;18</td>
<td>-0.106</td>
<td>(0.210)</td>
<td>-0.417</td>
</tr>
<tr>
<td>Share of family member aged&gt;60</td>
<td>-0.416*</td>
<td>(0.231)</td>
<td>0.434</td>
</tr>
<tr>
<td>Year 2009 (dummy)</td>
<td>-0.116</td>
<td>(0.072)</td>
<td>-0.531**</td>
</tr>
<tr>
<td>Constant</td>
<td>3.210***</td>
<td>(0.808)</td>
<td>0.569</td>
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<table>
<thead>
<tr>
<th>Individual fixed effect?</th>
<th>N</th>
<th>Y</th>
</tr>
</thead>
<tbody>
<tr>
<td>Observations</td>
<td>1,920</td>
<td>1,920</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.071</td>
<td>0.059</td>
</tr>
<tr>
<td>Number of individuals</td>
<td>960</td>
<td></td>
</tr>
</tbody>
</table>

Notes: The first two columns report the regression results of pooled OLS estimation. The last two columns report the regression result of individual fixed effect estimation. The coefficients and standard errors of dummy of male and age are not available for individual fixed effect estimation, since these variables are either constant or increase by the same amount over time. Omitted category for education is the group of person with less than primary school education. Both regressions are estimated using inverse probability weights to adjust for sample selection and attrition. Standard errors in brackets are clustered in households. *** p<0.01, ** p<0.05, * p<0.1.
### Table 3: Permanent and Transitory Income Shocks and SWB

<table>
<thead>
<tr>
<th></th>
<th>Dependent variable: change in global life satisfaction</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
</tr>
<tr>
<td>Permanent income shock (\beta_1)</td>
<td>0.030**</td>
</tr>
<tr>
<td></td>
<td>[0.013]</td>
</tr>
<tr>
<td>Transitory income shock (\beta_2)</td>
<td>0.002</td>
</tr>
<tr>
<td></td>
<td>[0.009]</td>
</tr>
<tr>
<td>Village fixed effect?</td>
<td>Y</td>
</tr>
<tr>
<td>p value of Wald test on (\beta_1&lt;=\beta_2)</td>
<td>0.0295</td>
</tr>
<tr>
<td>Observations</td>
<td>960</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.372</td>
</tr>
</tbody>
</table>

### Notes:

1) Permanent income shock is measured as the difference between expectation of future income positions in the village reported in years 2009 and that in year 2006. Transitory income shock is measured as the difference between realization of income position in village in year 2009 and expectation of future income positions in the village reported in year 2009. The expected income is adjusted to account for outlook bias, which we measured as the difference between actual income rank (construct by the rank of household income per capita in the village) and self-reported income rank in the village in the baseline year 2006.

2) The sample used for the regressions are from the year 2009. In all regressions, we control for change of the control variables in Table 2 and wealth variables, and lagged global life satisfaction. The regressions are estimated using inverse probability weights to adjust for sample selection and attrition.

3) Standard errors in brackets are clustered in households. *** p<0.01, ** p<0.05, * p<0.1.
Table 4: Explain Differences in Cross-sectional and Panel Regressions

<table>
<thead>
<tr>
<th></th>
<th>SWB (1)</th>
<th>Change in SWB (2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Income (rank in village) ((\phi))</td>
<td>0.043***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.009]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Lifetime income ((\phi'))</td>
<td>0.051***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.009]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Transitory income shock ((\phi''))</td>
<td>0.027***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.010]</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Change in income (rank in village) ((\lambda))</td>
<td></td>
<td>0.019**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.009]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Permanent income shock ((\lambda_1'))</td>
<td></td>
<td>0.041***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.015]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Change in transitory income shocks ((\lambda_2'))</td>
<td></td>
<td>0.016*</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>[0.009]</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Village-year fixed effect?</td>
<td>Y</td>
<td>Y</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Village fixed effect?</td>
<td>Y</td>
<td>Y</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Comparing coefficients between equations

- p value of Wald test on \(\phi = \lambda\) F(1, 779) = 5.89; Prob > F = 0.0155
- p value of Wald test on \(\phi' = \lambda_1'\) F(1, 779) = 0.40; Prob > F = 0.5265
- p value of Wald test on \(\phi'' = \lambda_2'\) F(1, 779) = 2.17; Prob > F = 0.1409

Comparing coefficients within equations

- p value of Wald test on \(\phi_1' \leq \phi_2', \text{or} \ \lambda_1' \leq \lambda_2'\) 0.0034 0.0390

Observations

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1,920</td>
<td>1,920</td>
<td>960</td>
<td>960</td>
<td></td>
</tr>
</tbody>
</table>

Notes:

1) Income is measured as the realized income position in the village. Transitory and permanent income shocks have the same definition as in Table 3. Lifetime income is measured as the difference between income (rank in village) and transitory income shock. Change in transitory income shocks is measured as the difference between transitory income shocks identified in years 2009 and 2006.

2) Regressions (1) and (2) include the same control variables as in Table 2. Village-year fixed effect is included to account for year specific unobservables of village income distribution. Regressions (3) and (4) include the same control variables as in Table 3 except for changes in wealth variables. All regressions are estimated using inverse probability weights to adjust for sample selection and attrition.

3) Standard errors in brackets are clustered in households. *** p<0.01, ** p<0.05, * p<0.1.
### Table 5: Calibration of the Parameters from the Data

#### Panel A: Variance-Covariance Matrices

<table>
<thead>
<tr>
<th></th>
<th>$x_t$</th>
<th>$x_t^p$</th>
<th>$\delta_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$x_t$</td>
<td>7.6695</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$x_t^p$</td>
<td>5.2173</td>
<td>10.5714</td>
<td></td>
</tr>
<tr>
<td>$\delta_t$</td>
<td>2.4522</td>
<td>-5.3541</td>
<td>7.8063</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th></th>
<th>$\Delta x_t$</th>
<th>$\eta_t$</th>
<th>$\Delta \delta_t$</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\Delta x_t$</td>
<td>10.8836</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\eta_t$</td>
<td>1.1620</td>
<td></td>
<td></td>
</tr>
<tr>
<td>$\Delta \delta_t$</td>
<td>9.7216</td>
<td>-4.6635</td>
<td>14.3851</td>
</tr>
</tbody>
</table>

#### Panel B: Calibration of the weights

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>unadjusted</td>
<td>0.6803</td>
<td>0.6747</td>
</tr>
<tr>
<td>adjusted</td>
<td>0.1068</td>
<td>0.1162</td>
</tr>
</tbody>
</table>

Notes: Panel A reports the calibration results of the variance-covariance matrices from the data. The first lower triangular matrix is the estimated variance-covariance matrix of income, lifetime income, and transitory income shock of the two year data. The second lower triangular matrix is the estimated variance-covariance matrix of change in income, permanent income shock, and change in transitory income shock between the two years. Panel B reports the calibration of the weights $w_c$ and $w_p$. By construction, $\omega_c = (\hat{\sigma}_p + \hat{\sigma}_p\delta)/\hat{\sigma}_x$ in the absence of control variables (column 1); $\omega_c = (\hat{\sigma}_p + \hat{\sigma}_p\delta)/\hat{\sigma}_x + (\hat{\theta}' - \hat{\theta}) \cdot \gamma/(\hat{\phi}_1' - \hat{\phi}_2')$ and $\omega_p = (\hat{\sigma}_\eta + \hat{\sigma}_\eta\delta)/\hat{\sigma}_\delta + (\hat{P}' - \hat{P}) \cdot \tau/(\hat{\lambda}_1' - \hat{\lambda}_2')$ when they are adjusted by control variables (column 2).
### Table 6: Credit Accessibility and Heterogeneous Effect of Income Shocks

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dependent variable:</strong> change in global life satisfaction</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Permanent income shock ($\beta_1$)</td>
<td>0.038***</td>
<td>0.062***</td>
</tr>
<tr>
<td></td>
<td>[0.014]</td>
<td>[0.020]</td>
</tr>
<tr>
<td>High asset × Permanent income shock</td>
<td>-0.025</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.040]</td>
<td></td>
</tr>
<tr>
<td>Transitory income shock _neg ($\beta_2_neg$)</td>
<td>0.026*</td>
<td>0.045**</td>
</tr>
<tr>
<td></td>
<td>[0.013]</td>
<td>[0.021]</td>
</tr>
<tr>
<td>High asset × Transitory income shock _neg</td>
<td>-0.055*</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.029]</td>
<td></td>
</tr>
<tr>
<td>Transitory income shock _pos ($\beta_2_pos$)</td>
<td>-0.010</td>
<td>0.001</td>
</tr>
<tr>
<td></td>
<td>[0.020]</td>
<td>[0.028]</td>
</tr>
<tr>
<td>High asset × Transitory income shock _pos</td>
<td>-0.039</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.028]</td>
<td></td>
</tr>
<tr>
<td>High asset</td>
<td>-0.020</td>
<td></td>
</tr>
<tr>
<td></td>
<td>[0.127]</td>
<td></td>
</tr>
<tr>
<td>Village fixed effect?</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>p value of Wald test on $\beta_1$&lt;=$\beta_2_neg$</td>
<td>0.2309</td>
<td></td>
</tr>
<tr>
<td>p value of Wald test on $\beta_1$&lt;=$\beta_2_pos$</td>
<td>0.0144</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>960</td>
<td>960</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.375</td>
<td>0.380</td>
</tr>
</tbody>
</table>

Notes:

1) High asset is a dummy indicating high values of asset index, which is constructed by principal-component factor of log of house value per capita, log of value of livestock per capita, and dummies of a couple of durables (large furniture, bicycler, motorbike, electric battery vehicle, radio/recorder, black and white TV, color TV, telephone, mobile phone, audiovisual products, refrigerator, air conditioning, gas stove, sewing machine, camera, washing machine, electric/solar water heater, computer, dispenser, microwave, agricultural motor vehicle, and car/truck).

2) The sample used for the regressions are from the year 2009. All regressions includes the same control variables as in Table 3, and are estimated using inverse probability weights to adjust for sample selection and attrition.

3) Standard errors in brackets are clustered in households. *** p<0.01, ** p<0.05, * p<0.1.
Table 7: Life Span and Heterogeneous Effects of Income shocks

<table>
<thead>
<tr>
<th></th>
<th>Young (21-45 years old)</th>
<th>Old (46-60 years old)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
</tr>
<tr>
<td>Permanent income shock ($\beta_1'$)</td>
<td>0.038</td>
<td>0.055***</td>
</tr>
<tr>
<td></td>
<td>[0.024]</td>
<td>[0.019]</td>
</tr>
<tr>
<td>Transitory income shock ($\beta_2'$)</td>
<td>0.004</td>
<td>0.029**</td>
</tr>
<tr>
<td></td>
<td>[0.018]</td>
<td>[0.012]</td>
</tr>
<tr>
<td>Village fixed effect?</td>
<td>Y</td>
<td>Y</td>
</tr>
<tr>
<td>$p$ value of Wald test on $\beta_1' \leq \beta_2'$</td>
<td>0.0452</td>
<td>0.0943</td>
</tr>
<tr>
<td>Observations</td>
<td>401</td>
<td>559</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.610</td>
<td>0.375</td>
</tr>
</tbody>
</table>

Notes:

1) The sample are from the year 2009, which are divided into two subgroups by the age of household head. Each column reports regression results of one subsample. All regressions includes the same control variables as in Table 3, and are estimated using inverse probability weights to adjust for sample selection and attrition.

2) Standard errors in brackets are clustered in households. *** p<0.01, ** p<0.05, * p<0.1.
Appendix

Figure A1: Prediction Power of Subjective Relative Income on Absolute Income

Note: The predicted values are from the regressions $x_{ij,t+1} = \sum_j \beta_j X_{ij,t} + \nu + \epsilon_{iv,t+1}$, where $x_{ij,t+1}$ is the log income per capita of household $i$ in village $j$ at time $t + 1$, $X$ is the constructed relative income position in village in Panel A, the self-reported relative income in Panel B, the expected relative income in Panel C, the adjust-expected relative income in Panel D (adjusted for outlook bias measured as the difference between constructed and subjective relative income rank in baseline year 2006). All regressions are estimated using inverse probability weights (IPW) to adjust for sample selection and attrition. Each panel plots the scatter of predicted and actual values of the log income per capita in year 2009, as well as a 45 degree line. The size of the markers are scaled according to the size of the weights constructed by IPW method. Each panel also contains the R-squared of the regression specified above.
Table A1: Mean Difference in Individual Characteristics between (Un)weighted Analysis Sample and Total Sample

<table>
<thead>
<tr>
<th>Individual characteristics</th>
<th>Total sample (1)</th>
<th>Analysis sample unadjusted (2)</th>
<th>Analysis sample adjusted (3)</th>
<th>Difference in Means (p values) (2)&amp;(1)</th>
<th>(3)&amp;(1)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>36.11</td>
<td>44.15</td>
<td>36.72</td>
<td>8.03</td>
<td>0.60</td>
</tr>
<tr>
<td></td>
<td>[12.16]</td>
<td>[8.73]</td>
<td>[13.72]</td>
<td>(0.000)</td>
<td>(0.170)</td>
</tr>
<tr>
<td>Male (dummy)</td>
<td>0.51</td>
<td>0.37</td>
<td>0.59</td>
<td>-0.14</td>
<td>0.08</td>
</tr>
<tr>
<td></td>
<td>[0.50]</td>
<td>[0.48]</td>
<td>[0.49]</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Married (dummy)</td>
<td>0.75</td>
<td>0.97</td>
<td>0.71</td>
<td>0.22</td>
<td>-0.04</td>
</tr>
<tr>
<td></td>
<td>[0.43]</td>
<td>[0.16]</td>
<td>[0.45]</td>
<td>(0.000)</td>
<td>(0.016)</td>
</tr>
<tr>
<td>Less than primary school education (dummy)</td>
<td>0.19</td>
<td>0.33</td>
<td>0.20</td>
<td>0.14</td>
<td>0.01</td>
</tr>
<tr>
<td></td>
<td>[0.39]</td>
<td>[0.47]</td>
<td>[0.40]</td>
<td>(0.000)</td>
<td>(0.352)</td>
</tr>
<tr>
<td>Primary school education (dummy)</td>
<td>0.25</td>
<td>0.30</td>
<td>0.25</td>
<td>0.04</td>
<td>0.00</td>
</tr>
<tr>
<td></td>
<td>[0.44]</td>
<td>[0.46]</td>
<td>[0.44]</td>
<td>(0.005)</td>
<td>(0.959)</td>
</tr>
<tr>
<td>Middle school education (dummy)</td>
<td>0.39</td>
<td>0.28</td>
<td>0.28</td>
<td>-0.11</td>
<td>-0.12</td>
</tr>
<tr>
<td></td>
<td>[0.49]</td>
<td>[0.45]</td>
<td>[0.45]</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>High/vocational school education (dummy)</td>
<td>0.13</td>
<td>0.09</td>
<td>0.24</td>
<td>-0.04</td>
<td>0.11</td>
</tr>
<tr>
<td></td>
<td>[0.33]</td>
<td>[0.28]</td>
<td>[0.43]</td>
<td>(0.001)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>College education or above (dummy)</td>
<td>0.04</td>
<td>0.01</td>
<td>0.03</td>
<td>-0.03</td>
<td>-0.01</td>
</tr>
<tr>
<td></td>
<td>[0.19]</td>
<td>[0.09]</td>
<td>[0.17]</td>
<td>(0.000)</td>
<td>(0.282)</td>
</tr>
</tbody>
</table>

Notes: The summary statistics reported in the table are of baseline year 2006. Column (1) reports the mean and standard deviation (in the brackets) of the total household members who are eligible to answer the subjective questions in both years (aged between 18 and 57). The sample size is 4702. Information on education are missing for 10 of the observations. Columns (2) and (3) report the summary statistics for the sample used in our main analysis, with a sample size of 960. Results in column (3) are estimated using inverse probability weights to adjust for sample selection and attrition, while results in column (2) are not. The last two columns reports the difference in means and p values of t tests on equality of means (in the parentheses) between columns (1) and (2), and between columns (1) and (3).
Table A2: Accounting for Measurement Error in Income

<table>
<thead>
<tr>
<th>Dependent variable: global life satisfaction</th>
<th>Reduced form regression</th>
<th>IV regression</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Pooled cross-section</td>
<td>Panel</td>
</tr>
<tr>
<td></td>
<td>coef.</td>
<td>s.e.</td>
</tr>
<tr>
<td>Log of household income per capita</td>
<td>0.258***</td>
<td>(0.258)</td>
</tr>
<tr>
<td>Predicted log of household income per capita</td>
<td>0.076**</td>
<td>(0.076)</td>
</tr>
<tr>
<td>Age</td>
<td>-0.052*</td>
<td>(0.052)</td>
</tr>
<tr>
<td>(Age/10)^2</td>
<td>0.005</td>
<td>(0.005)</td>
</tr>
<tr>
<td>Male (dummy)</td>
<td>-0.139*</td>
<td>(0.139)</td>
</tr>
<tr>
<td>Married (dummy)</td>
<td>0.006</td>
<td>(0.006)</td>
</tr>
<tr>
<td>Education=primary school</td>
<td>0.141*</td>
<td>(0.141)</td>
</tr>
<tr>
<td>Education=high/vocational school</td>
<td>0.391***</td>
<td>(0.391)</td>
</tr>
<tr>
<td>Education=college or above</td>
<td>0.390</td>
<td>(0.390)</td>
</tr>
<tr>
<td>Household size</td>
<td>0.021</td>
<td>(0.021)</td>
</tr>
<tr>
<td>Number of migrants in household</td>
<td>0.025</td>
<td>(0.025)</td>
</tr>
<tr>
<td>Share of family member aged&lt;18</td>
<td>-0.112</td>
<td>(-0.112)</td>
</tr>
<tr>
<td>Share of family member aged&gt;60</td>
<td>-0.394*</td>
<td>(-0.394)</td>
</tr>
<tr>
<td>Year 2009 (dummy)</td>
<td>-0.139**</td>
<td>(-0.139)</td>
</tr>
<tr>
<td>Constant</td>
<td>2.314**</td>
<td>(2.314)</td>
</tr>
</tbody>
</table>

Individual fixed effect? | N | Y | N | Y |
F statistic of weak IV test | 450.01 | 116.48 |
Observations | 1,920 | 1,920 | 1,920 | 1,920 |
R-squared | 0.078 | 0.058 | 0.058 | 0.056 |
Number of individuals | 960 | 960 | 960 | 960 |

Notes:
1) The predicted log of household income per capita are the predicted values from self-reported relative income by the model specified in Figure A1.

2) The first four columns report the pooled OLS regression and individual fixed effect regression of global life satisfaction on the predicted log of household income per capita. The last four columns reported the instrumental variable estimation for the cross-section and panel regression of the global life satisfaction on log of household income per capita, where the instrument is the predicted log of household income per capita from self-reported relative income.

3) The coefficients and standard errors of dummy of male and age are not available for individual fixed effect estimation, since these variables are either constant or increase by the same amount over time. The Stata command-xivreg2 which we used for the panel-IV estimation does not report a constant with the fixed effects model. Omitted category for education is the group of person with less than primary school education. All regressions are estimated using inverse probability weights to adjust for sample selection and attrition. Standard errors in parentheses are clustered in households. *** p<0.01, ** p<0.05, * p<0.1.
<table>
<thead>
<tr>
<th></th>
<th>Pooled cross-section</th>
<th>Panel</th>
<th>Pooled cross-section</th>
<th>Panel</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>coef.</td>
<td>s.e.</td>
<td>coef.</td>
<td>s.e.</td>
</tr>
<tr>
<td>Log of household income per capita</td>
<td>0.125***</td>
<td>(0.035)</td>
<td>0.036</td>
<td>(0.047)</td>
</tr>
<tr>
<td>Self-reported health status</td>
<td>0.174***</td>
<td>(0.037)</td>
<td>0.174***</td>
<td>(0.048)</td>
</tr>
<tr>
<td>Self-reported income rank in village</td>
<td></td>
<td></td>
<td>0.036</td>
<td>(0.047)</td>
</tr>
<tr>
<td>Age</td>
<td>-0.058*</td>
<td>(0.030)</td>
<td>n.a.</td>
<td>n.a.</td>
</tr>
<tr>
<td>(Age/10)^2</td>
<td>0.088**</td>
<td>(0.035)</td>
<td>0.220***</td>
<td>(0.083)</td>
</tr>
<tr>
<td>Male (dummy)</td>
<td>-0.138**</td>
<td>(0.069)</td>
<td>n.a.</td>
<td>n.a.</td>
</tr>
<tr>
<td>Married (dummy)</td>
<td>0.075</td>
<td>(0.155)</td>
<td>-0.121</td>
<td>(0.212)</td>
</tr>
<tr>
<td>Education=primary school</td>
<td>0.003</td>
<td>(0.072)</td>
<td>0.018</td>
<td>(0.118)</td>
</tr>
<tr>
<td>Education=middle school</td>
<td>0.100</td>
<td>(0.072)</td>
<td>0.173</td>
<td>(0.151)</td>
</tr>
<tr>
<td>Education=high/vocational school</td>
<td>0.298**</td>
<td>(0.128)</td>
<td>-0.009</td>
<td>(0.250)</td>
</tr>
<tr>
<td>Education=college or above</td>
<td>0.339</td>
<td>(0.302)</td>
<td>-0.120</td>
<td>(0.320)</td>
</tr>
<tr>
<td>Household size</td>
<td>0.021</td>
<td>(0.030)</td>
<td>-0.030</td>
<td>(0.037)</td>
</tr>
<tr>
<td>Number of migrants in household</td>
<td>0.018</td>
<td>(0.037)</td>
<td>-0.022</td>
<td>(0.048)</td>
</tr>
<tr>
<td>Share of family member aged&lt;18</td>
<td>-0.065</td>
<td>(0.212)</td>
<td>-0.273</td>
<td>(0.344)</td>
</tr>
<tr>
<td>Share of family member aged&gt;60</td>
<td>-0.547**</td>
<td>(0.243)</td>
<td>0.210</td>
<td>(0.374)</td>
</tr>
<tr>
<td>Year 2009 (dummy)</td>
<td>-0.147**</td>
<td>(0.064)</td>
<td>-0.636***</td>
<td>(0.241)</td>
</tr>
<tr>
<td>Constant</td>
<td>2.797***</td>
<td>(0.811)</td>
<td>-0.277</td>
<td>(1.270)</td>
</tr>
<tr>
<td>Individual fixed effect?</td>
<td>N</td>
<td>Y</td>
<td>N</td>
<td>Y</td>
</tr>
<tr>
<td>Observations</td>
<td>1,914</td>
<td>1,914</td>
<td>1,920</td>
<td>1,920</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.107</td>
<td>0.099</td>
<td>0.130</td>
<td>0.086</td>
</tr>
<tr>
<td>Number of individuals</td>
<td>960</td>
<td>960</td>
<td>960</td>
<td>960</td>
</tr>
</tbody>
</table>

Notes: This table reports results of regressions based on regressions in Table 2, and further control for self-reported health status (with five possible values: 1. very poor, 2. poor, 3. fair, 4. good, 5. very good) in columns 1 to 4, and self-reported income rank in village in columns 5 to 8. The coefficients and standard errors of dummy of male and age are not available for individual
estimation, since these variables are either constant or increase by the same amount over time. Omitted category for education is the group of person with less than primary school education. All regressions are estimated using inverse probability weights to adjust for sample selection and attrition. Standard errors in parentheses are clustered in households. *** p<0.01, ** p<0.05, * p<0.1.