Evaluating the propensity to save in South Africa using weather-income relationship

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Abstract

We study the propensity to save on permanent and transitory income base on a newly available, comprehensive household panel dataset from South Africa. We proxy transitory income by weather deviations from thirty-year normals, using daily temperature and precipitation data for the last 30 years. We evaluate the propensities to save by OLS and by median regressions. By OLS, we find that the propensity to save on transitory income is equal to 1, while the null hypothesis that the propensity to save on permanent income equal to 0 is rejected. This finding is in alignment with previous studies. By median regression, we reject the null that propensities to save by permanent or transitory income is equal to 0 or 1, meaning that the propensities to save represent some fractions of permanent and transitory income. We also evaluate the propensity to save by income quintiles using median regression. We find that the propensities to save from permanent and transitory income are only significantly different in the highest quintile, while not significantly different in the lower 80% of the income distribution. In the top 20%, we find the propensity to save by transitory income is significantly higher than that of permanent income, although it still does not reach unity.

1. Introduction

Weather can affect household saving in two ways. It directly impacts income for those sectors where there exists income sensitivity to weather. For example, agricultural income for those households engaged in rain-fed agriculture has been shown to be affected by weather. Furthermore, weather has also been shown to negatively impact economic activities that are sensitive to outdoor temperature (e.g., construction or mining) (Hsiang et al. (2017); Zivin and Neidell (2014)). Weather may also affect saving through household consumption, by influencing local and regional food prices (von Braun (2009)). In economic analyses, weather has been used as an exogenous predictor of transitory income, particularly in developing countries where large proportions of population are engaged in agriculture. It is therefore, reasonable to disaggregate income into its two components, permanent and transitory, using weather as a predictor of transitory income. This method is particularly fitting in regions where weather may have a stronger effect on income, such as those economies that rely on rain-fed agriculture, or activities related to outdoor labor.

In this paper, we evaluate weather as an exogenous predictor to transitory income. Furthermore, we examine household's propensity to save on permanent and transitory income with recent, nation-wide data from South Africa. We decompose income into permanent and transitory components (Friedman (1957); Jappelli and Pistaferri (2010); Modigliani and Brumberg (1954)) where permanent income is proxied by household assets and demographic structure, and transitory income is predicted with seasonal weather variations from 30-year climate normals (Paxson (1992)). The estimated effect of saving on permanent and transitory income represent the respective propensities to save. We develop point estimates from both OLS and median regression, and compare these estimates to theoretically derived predictions. We further evaluate the propensities to save by income distribution in order to identify any differential effect of income inequality.

We are able to conduct such analysis, due to the large sample size of the nationally representative panel data we have from the National Income Dynamic Study of South Africa (NIDS (2016)). The four panels we use in the dataset cover the period from 2008 to 2014. This household survey includes over 6,000 households across 9 provinces and 52 districts of South Africa. The sampling is statitically weighted to represent the distribution of South Africa's population. We combine this comprehensive household dataset with daily weather data (e.g., temperature and precipitation) from European Centre for Medium-Range Weather Forecasts ERA-Interim dataset (Dee et al. (2011)). We link the datasets with geopositioning data of households at the district level, which is the most disaggregated level that is available to us in the publically available dataset.

We introduce three novelties through this paper. First, our household data is comprehensive and novel. We use a nationally representative household dataset from recent periods from a developing country, with high levels of income inequality. According to the World Bank and Statistics South Africa, our sample country, South Africa has a Gini coefficient of 0.63 in 2015, based on expenditure data, one of the highest in the world. The bottom 60% of the South African population held 7% of total wealth, while the wealthiest 10% held about 71% (WorldBank (n.d.-b)). Second, we leverage comprehensive, 30-year weather data at the resolution of 0.75-by-0.75 degrees (about 80km by 60km) from climate reanalysis dataset as an exogenous source of heterogeneity. This gives us an estimate of the effect of weather on income, which is of particular relevance in South Africa, as it is predicted to suffer from warming according to IPCC (Niang et al. (2014)). Third, we compare propensity to save from linear regression versus median regression, taking into account the non-normality of the residuals after ordinary least square (OLS). We also evaluate results of median regression by income quintiles to assess differential effects by income groups.

We find that the propensity to save by linear regression corresponds well with theoretical prediction and previously reported results, where marginal saving out of transitory income is close to unity (when durable goods are considered saving). The marginal saving out of permanent income is not zero, indicating some portion of the permanent income is also saved. By median regression, we find a lower propensity to save than linear regression. We also reject the hypothesis that the propensity to save from transitory income is close to unity. By income groups, our finding suggest that the treatment of durable goods leads to different results. When durable goods are considered as consumption, the propensities to save do not differ significantly across quintiles, leading to a consistent marginal savings rate across the income distribution. When durable goods are considered as part of saving, we find a higher marginal saving rate for the higher income quintile versus the lower income group. Thus, we draw a preliminary conclusion that durable good consumption may serve as a means of value perservation among the higher income households in South Africa.

For the remainder of this paper, we discuss a review of relevant literature in Section 2. We present a summary of the theoretical model of inter-temporal consumption and saving to guide our empirical analysis in Section 3. In section 4, we discuss our data. In section 5, we outline our empirical approach. Section 6 is the presentation of our results, and section 7 concludes.

2. Literature review

The literature on the propensity to consume and save is vast and well established. In this section, we selectively highlight some of the results, as they are relevant to the theoretical understanding of our analysis.

Weather as a predictor of income

The use of weather as an exogenous predictor of income is well documented. The most recognized pathway by which weather can affect income is through its direct impact on agricultural conditions, which affects yield. A recent systematic review of changes in crop yields under climate change across Africa and South Asia found that yields may decline by 8 percent across both regions by 2050 due to changes in weather patterns (Knox, Hess, and Daccache (2012)). In economic evaluations, Wolpin (Wolpin (1982)) used long-term annual rainfall data in India to estimate the permanent income elasticity of consumption, arguing that long-term stable weather conditions is a source of heterogeneity in permanent income among traditional farming households. Paxson (Paxson (1992)) used time-series information on deviation from average of regional rainfall as an explicit measure of transitory income in her evaluation of the propensity to save, while she measured permanent income with household demographic characteristics and asset levels. Hirvonen (Hirvonen (2016)) estimated coefficients of temperature and rainfall on log-consumption in his evaluation of the effect of temperature change on consumption and migration. Another, less studied pathway by which weather can affect income and consumption is through its indirect effect on food prices in the local, regional, or even global markets (Wheeler and von Braun (2013)). It is postulated that small shocks on the supply or demand of food can have large impacts on prices (von Braun (2009)). This, however, has not been sufficiently studied, both in macroeconomic modelling and microeconomic studies based on panel datasets (Headey and Fan (2008)). Furthermore, using weather as a predictor of transitory income as in previously cited studies has the limitation of ignoring unpaid family labor in an agricultural setting. Such omission may present a biased estimate of income effects on consumption that depends on labor-supply behavior and on the completeness of labor markets, which may lead to inappropriate acceptance of the null hypothesis in favor of perfect consumption smoothing (Rosenzweig (2001)).

In countries like South Africa, where weather-impacted labor such as construction and mining represent a significant portion of household livelihood, increased weather variability represent a particular source of vulnerability to stable consumption and food security (Bryan, Deressa, Gbetiboubo, and Ringler (2009); Hsiang et al. (2017); Karfakis, Lipper, and Smulders (2012)). Weather variability affects farmers engaged in rain-fed crop production, which is predominant in many African countries (Bozzola, Smale, and DiFalco (2016); Hirvonen (2016); Kurukulasuriya and Mendelsohn (2008)). In a low-income setting, Rosenzweig and Wolpin (Rosenzweig and Wolpin (1993)) showed that without insurance and constrained by credit, those with low average income (i.e., small and medium size farms) cannot effectively smooth consumption based on asset transactions (i.e., bullocks). In rural Burkina Faso during a period of severe draught (1981 to 1985), for example, it was found that rural households exhibited little consumption smoothing and households relied almost exclusively on self-insurance in the form of grain stock adjustments (Kazianga and Udry (2006)). Studying the effect of weather on consumption and the consequent impact on labor migration in Tanzania, Hirvonen (Hirvonen (2016)) found that a standard deviation increase in mean temperature of the previous growing season led to a 5% decrease in household consumption, and a 13% decrease in male migration. This reduction in migration is attributed to potential liquidity constraints due to temperature change.

Consumption and saving responses to income

Our theoretical framework is related to consumption and saving responses to income change as put forth in the standard permanent income hypothesis (Friedman (1957); Jappelli and Pistaferri (2010); Modigliani and Brumberg (1954)) and buffer stock model (Deaton (1989, 1991)). According to the permanent income hypothesis, if real interest rate is equal to the discount rate, and agents exhibit quadratic preferences and are risk neutral, the optimal consumption path is one of consumption smoothing, where consumption in each period is equivalent to lifetime average of future income. If income can be decomposed into a permanent, deterministic component, and an independent and identically distributed (i.i.d) transitory component, then the propensity to consume out of permanent income should be close to unity, while the propensity to consume out of transitory income should be close to zero (Jappelli and Pistaferri (2010)). Thus, the permanent income hypothesis suggests that consumption is smoothed over the lifetime, and is a constant proportion of an individual's lifetime permanent income (Friedman (1957); Modigliani and Brumberg (1954)). The buffer-stock model introduces impatience, prudence and credit constraint, by assuming that the discount rate is greater than the real interest rate, and agents exhibit utility functions such that the marginal utility is (strictly) convex. When future income follows an i.i.d process, or an autoregressive process with coefficent less than unity, consumption behaves as a non-linear function of assets and income, where the propensity to consumer above the break point is less than unity (Deaton (1989, 1991)).

Early empirical studies of propensity to consume mostly found a less than unity coefficient on permanent income (Bhalla (1979, 1980); Musgrove (1979, 1980)). Wolpin (Wolpin (1982)) found the permanent income elasticity of consumption to be close to unity, measuring household heterogeneity in permanent income with long-term average rainfall in Indian farming household. Paxson (Paxson (1992)) studied the saving behavior of Thai rice farmers using weather variability as a measure of transitory income and found that a significant portion of transitory income is saved, although some permanent income is also saved. Empirical evidence on the importance of precautionary saving provides mixed results. While some studies have found a limited role of precautionary saving in wealth accumulation, others have found a larger role. Jappelli, Padula and Pistaferri (Japelli, Padula, and Pistaferri (2008)) conducted a test of precautionary motive in Italian households, leveraging a direct question in the survey questionnaire that asked how much savings they think they need for future emergencies. They found that the ratio of covariance between wealth gap and consumption, and that of wealth gap and income is much lower than what would be predicted from the buffer-stock model, both across the whole population, and in groups that would seem to exhibit buffer-stock like behavior. Their finding suggests a more steady consumption path relative to future expectations of income than what would be predicted from the buffer-stock model.

Heterogeneous responses by income distribution

A related question is whether differences exist in saving behavior across income quantiles. Several theory extensions seek to explain the complex relationship between income and saving across income distribution, specifically the positive correlation between income and saving at the national level. An early theory (Kaldor (1957); Lewis (1954)) suggests that individual propensity to save is less than firm's, such that higher aggregate saving reflects firm's higher propensity to save, not individuals. Empirical studies based on cross-sectional micro-data in general have found that saving rates increases with current income while aggregate saving and income studies offer mixed results. Della Valle and Oguchi (DellaValle and Oguchi (1976)) found no statistically significant effect of income distribution on saving, except for OECD countries. Lim (Lim (1980)) found inequality tend to raise aggregate saving rate in a cross-sectional sample of developing countries. Using data from 49 countries, Venieris and Gupta (Venieris and Gupta (1986)) found poorer household have the lowest saving propensities while the highest ones corresponds to the middle-income group. Cook (Cook (1995)) estimated the impact of various inequality measures on the GDS/GDP ratio in 49 least developed countries (LDCs), and found significant positive effect of inequality on saving. Using annual cross-sectional time-series data for the 1965-1994 period from the World Bank, Schmidt-Hebbel and Serven found no significant relationship between income inequality and aggregate saving (Schmidt-Hebbel and Serven (2000)). Bunting (Bunting (1991)) found evidence that households' marginal propensity to save uniformly increases as their quintile share of income rises. Using data from the US, Dynan (Dynan, Skinner, and Zeldes (2004)) found strong positive relationship between income quintile and average saving rate, and a weaker, albeit positive relationship with marginal saving rate. Some studies suggest a bequeath motive among the rich which explains the higher saving rate among higher income quantiles (Carroll (1998)). Kopczuk (Kopczuk and Lupton (2007)) found that roughly 75% of elderly households in the US have a bequest motive, and they spend 25% less on personal outlays on average. A further explanation is precautionary saving, where individuals in lower income quartiles depress current consumption, leading to a higher marginal propensity to consume (Carroll and Kimball (1996)).

Rosenzweig et al. (Rosenzweig (2001)) outlined three characteristics where the study of saving in developing countries differ from high income countries. First, due to the lower income level in such countries relative to the minimal standards for living, opportunities for sustained saving is limited. Second, agriculture tend to be a larger share of economic activity, and it is a less predictable income source that is subject to fluctuation in conditions such as weather. Third, there is usually a lack of a well-functioning insurance and credit market. Thus, households in developing economies are faced with the challenge of maintaining consumption while income is low and highly variable (Rosenzweig (2001)).

Literature on saving behavior in South Africa

Several studies have recently examined saving behavior in South Africa. Zwane et al. (Zwane, Greyling, and Maleka (2016)) studied the effect of income on saving in South Africa using the first three waves of NIDS. They included province level fixed effects, and also an instrument variable approach using lagged income in their evaluation of the effect of income on saving. They found a strong positive effect of income on saving while the effect of household size is in the negative direction. Bengtsson (Bengtsson (2012)) estimated the propensity to consume in South Africa out of unearned income, leveraging the introduction of an unconditional child support grant. The marginal propensity to consume was estimated to be 0.7 in this case while the marginal propensity to save seems to be close to zero (or even negative against future grant payments). Ting and Kollamparambil (Ting and Kollamparambil (2015)) looked at saving behavior in South African households using the General Household Survey (2002-2004 and 2008-2010). Their findings suggest that government grants not only sustain household consumption, but also household saving, as the consumption-income ratio seem to be smooth over age cohorts.

3. Theoretical framework

In this section, we present a summary of the theoretical framework of rational consumption response to income changes for a representative household (Deaton (1989); Jappelli and Pistaferri (2010)). We assume a unitary household model, and do not consider intra-household dynamics.

In this sample of South African households, only about 30% of the individuals have primary income through employment. This implies that household income typically represents income from a minority of household members, while consumption is shared among the household. We do not have sufficiently granular data, however, to identify separate consumption and saving by household member. Therefore, we consider the household as a unit of analysis, with household income and consumption as the main variables of analysis.

Consider the standard model of a household agent who maximizes the expected utility of consumption over some time period, subject to an inter-temporal budget constraint and a terminal condition on wealth. In each period t, the household agent i receives income $y_{it} = \overline{y_{it}} + \epsilon_{it}$, where $\overline{y_{it}}$ is deterministic and ϵ_{it} represent shocks with $E(\epsilon_{it}) = 0$. The agent chooses consumption c_{it} to maximize remaining lifetime expected utility $E_{it}(\sum_t^\infty (1+\delta)^{-t} u(c_{it}))$, subject to the budget constraint $w_{it} = (1+r_t)(w_{i,t-1} + y_{it} - c_{it})$ where w_t is wealth in period t, and y_t is income in period t. r is the fixed real interest rate, $\delta > 0$ is the rate of time preference, c_{it} is household consumption, and $u(c_{it})$ is the instantaneous utility associated with consumption c_{it}. If the utility function is time-separable, then the Euler equation becomes:

$$u'(c_{it}) = E_t[\frac{(1+r_t)u'(c_{i,t+1})}{(1+\delta)}] \tag{1}$$

As in the standard model, a quadratic utility function, which assumes a constant marginal utility of consumption, gives the permanent income model with certainty equivalence (Campbell (1987); Flavin (1981); Jappelli and Pistaferri (2010)). If the discount rate and interest rate are constants and equal to each other, the Euler equation is:

$$c_{i,t+1} = c_{i,t} + \epsilon_{i,t+1} \tag{2}$$

where $\epsilon_{i,t+1} = c_{i,t+1} - E_t c_{i,t+1}$ is the consumption modifier that adjusts based on new information about uncertainties faced by the agent. Assuming labor income uncertainty in the future periods, changes in consumption from period $t+1$ to t becomes:

$$\Delta c_{it} = \frac{r}{1+r} \sum_{\tau=0}^{\infty} (1+r)^{-\tau} (E_t - E_{t-1}) y_{i,t+\tau} \tag{3}$$

where $r/(1+r)$ is the annuity factor under the assumption of infinite horizon. If income can be decomposed into a permanent component, $P_{it} = P_{i,t-1} + u_{it}$ and an independent and identically distributed (i.i.d) transitory component v_{it}, then

$$\Delta c_{it} = \frac{r}{1+r} v_{it} + u_{it} \tag{4}$$

In this case, the model predicts that consumption responds one-to-one to permanent income shocks but is nearly insensitive to transitory shocks. Furthermore, as shown by Campbell (Campbell (1987)), the saving equation can be written as

$$s_{it} = \frac{1}{1+r} v_{it} \tag{5}$$

This identity implies that saving should respond to changes in transitory income but not permanent income (Jappelli and Pistaferri (2010)).

To incorporate precautionary saving, we assume that the utility function in Equation 1 is isoelastic, so that the agent is risk-averse. The marginal utility of the isoelastic utility function takes the form of $c^{-\rho}$. The parameter ρ controls the degree of precautionary saving. In this case, the instantaneous utility function u is three times differentiable and satisfies $u' > 0$,$u'' < 0$, and $u''' > 0$. The third derivative condition implies that the agent is a precautionary saver as the marginal utility is (strictly) convex (Berg (2013); Deaton (1989)). The marginal disutility of consumption losses at near subsistence is greater than gains in marginal utility during times of abundance. Agents will therefore give up some consumption in good times to save for those bad times, even if they are less frequent. Furthermore, we assume that the agents are credit constrained, in that she is not able to borrow sufficiently in times of need, such that

$$w_{it} \geq 0 \tag{6}$$

With the assumption that $\delta > r$ such that agents are impatient, so that the credit constraint will have an effect. Given the presence of credit constraint where the marginal utility of assets and income at time t is greater than the expected marginal utility of consumption at $t+1$, the Euler equation takes on the following form:

$$u'(c_{it}) = \max\ \{u'(w_{it} + y_{it}), E_t[\frac{(1 + r_t)u'(c_{i,t+1})}{(1 + \delta)}]\} \tag{7}$$

If income can be assumed to be independent and identitically distributed, then consumption graphed against cash-on-hand (assets and permanent income) shows a discontinuity. At lower levels of cash-on-hand, consumption traces cash-on-hand at a steeper slope, resulting in no saving or dissaving. The shape of the consumption curve as it relates to cash-on-hand is determined by the interaction of the credit constraint and the degree of precautionary saving. A stronger precautionary motive shifts the consumption curve lower (Deaton (1989)). Furthermore, saving will increase with relation to permanent income, leading to a less than unity propensity to consume in relation to permanent income (Deaton (1989)). In this model, consumption is a non-linear function of cash-on-hand (Deaton (1991)).

Paxson (Paxson (1992)) specified a testable form of the saving equation that is linear in permanent income, transitory income, and the variance of income. It is written as:

$$S_{irt} = \alpha_0 + \alpha_1 Y^P_{irt} + \alpha_2 Y^T_{irt} + \alpha_3 \mathrm{VAR}_{ir} + \alpha_4 W_{irt} + \epsilon_{irt} \tag{8}$$

where S_{irt} is saving for individual i, in region r, at time t. Y^P_{irt} represents the permanent portion of the individuals income, while Y^T_{irt} represents the transitory portion. VAR_{ir} represents income variation of individual i in region r, and W_{irt} is a set of household lifecycle characteristics.

The standard model predicts that α_1 should be close to zero, while α_2 should be close to one. The prediction of α_3 should be close to zero with a quadratic utility function as income variances do not factor into the saving equation with this utility function. If α_3 is greater than zero, then that is an indication of risk-aversion.

4. Data

We leverage two separate datasets for this analysis. The weather dataset is comprehensive climate data from 1979 to present day from European Centre for Medium-Range Weather Forecasts ERA-Interim dataset (Dee et al. (2011)). The household dataset is the National Income Dynamic Study of South Africa (NIDS (2016)).

4.1 Weather

We compile mean daily temperature and total daily precipitation data from ERA-Interim dataset (Dee et al. (2011)). This dataset provides a reanalysis of global atmosphere since 1979, on a 0.75-by-0.75 degrees resolution grid (about 80km by 80km). The ERA-Interim reanalysis is constructed from actual observations to provide a spatially complete and coherent record of global atmospheric circulation. This type of datasets is increasingly used by economists (Burgess, Deschenes, Donaldson, and Greenstone (2014); Colmer (2016a, 2016b)) as it can be a valuable alternative when studying geographies where weather observation stations are scarce and scattered with inconsistent reporting (Berrisford et al. (2011); Dee et al. (2011)).

We construct two sets of rainfall variables and three sets of temperature variables, matching weather data to each of South Africas 52 districts using GPS coordinates. For each panel dataset, we create a grid covering the entire geography of the country, with each grid representing a 0.75-by-0.75 degree GPS area. Within each grid, we further divide the area into quarters. We attribute district GPS to each of the four quarters within the grid, which covers all of South Africa at the most granular scale possible given the available GPS and climate data. See Table 2 and Appendix 8.1 for descriptive summary of weather.

We construct weather variables from GPS-matched climate data, according to planting, growing and non-agriculture seasons in South Africa (VAM (2016)). For rainfall, we calculate seasonal deviation from long-term norm as the difference between total seasonal rainfall and climatic normals. Normals are calculated as the average of total seasonal rainfall of the previous 30 years (from 1979 to 2008). We include a square term to account for non-linearity. We also construct the coefficient of variation by season to account for variation in the standard deviation, where coefficient of variation is the standard deviation of seasonal rainfall, divided by the mean. Similarly for temperature, we calculate the difference between mean seasonal temperature and temperature norm, and coefficient of deviation by season. We also include extreme events, captured by a variable that accounts for the number of days in the growing season when the temperature is above 34 degrees Celsius. Temperature above this level has been shown to be detrimental to crop growth (Hirvonen (2016)).

4.2 Household Panel

The National Income Dynamic Study (NIDS) of South Africa collects representative household consumption and income information in two-year increments, starting in 2008 (NIDS (2016)). The data is rich in individual and household characteristics, spending pattern, and health and education. This data has been used to study gender effects and food adequacy of subsistence farming in South Africa (Tibesigwa and Visser (2016); Tibesigwa, Visser, and Turpie (2015)), among others.

The NIDS follows a stratified, two-stage clustered sample design. Leibbrandt (Leibbrandt, Woolard, and de Villiers (2009)) provides detailed description of the sampling and data collection methodology. We present a summary in Appendix 8.2. Survey instruments were developed by South African Labor and Development Research Unit at School of Economics at the University of Cape Town. Quality control, such as back-to-the field rework, was built into the data collection process. The attrition rate (relative to the previous wave) for Wave 2 is 22%, for Wave 3 is 16% and for Wave 4 is 14% (Chinhema et al. (2016)).

Definition of key variables and descriptive statistics are provided in Table 1 and Table 2. Mean income for South African households over the study period is 3,708 South African Rand (SFR), with a standard deviation of 9,100 SFR (see Table 2). Median income is 1,834 SFR. Values for 25th percentile and 75th percentile are 975 SFR and 3,568 SFR, respectively.

Table 1: Definition of variables

Variable	Definition
Outcome variables	
Income	Total HH income from all sources in last 30 days
Consumption	Total consumption, including durable and non-durable, in last 30 days
Durable consumption	Expenditure in HH maintenance, kitchen, furniture, clothing, etc. in last 30 days
Non-durable consumption	Expenditure in food, utilities, and other personal consumption in last 30 days
Saving	Version 1: Income minus total consumption; Version 2: Income minus non-durable consumption
Permanent income factors	
Assets (in deciles)	Market value of owned house (rent=0), inheritances, and household reported net assets in deciles
Under 5yo	No of HH members under 5 years old
6-11yo, male / female	No of HH male/female members from 6 to 11 years old
12-17yo, male / female	No of HH male/female members from 12 to 17 years old

18-64yo, male / female, < 7 yrs of education	No of HH male/female members from 18 to 64 years old, with less than 7 years of education
18-64yo, male / female, 7-9 yrs of education	No of HH male/female members from 18 to 64 years old, with 7 to 9 years of education
18-64yo, male / female, >9 yrs of education	No of HH male/female members from 18 to 64 years old, with more than 9 years of education
>65yo, male / female	No of HH male/female members >65 years old
Transitory income factors	
Rainfall, deviation from mean (mm)	Total rainfall deviation from climate normal by season
Rainfall, coefficient of variation (σ/μ)	Rainfall std. dev. divided by mean in the same season
Temperature, deviation from mean (mm)	Seasonal mean deviation from climate normal
Temperature, coefficient of variation	Temperature std. dev. divided by mean in the same season
Days in growing season over 34deg C	No days in the growing season warmer than 34deg C

In the survey, each household is asked to estimate the income generated by members of the household in the previous 30 days. This includes all of household members salaries and wages, grants, interest, rental income and income from agriculture. Household either report the actual income figure, or indicate the range in which the household income falls. When income range is indicated, we take the median value for each range, and cap the income at the highest range. Average missingness across all four waves of the survey is 20.5%, and is within the range of typical household surveys (Kim, Egerter, Cubbin, Takahashi, and Braveman (2007)). Where household income is missing, we proxy by adding the individual income from members within the household.

We inflation-adjust income and consumption to take into account the fact that South Africa experienced significant inflation from the period of 2008 to 2014. By province, overall CPI ranges from 111.9 to 113.5 in 2010, 123.1 to 125.5 in 2012, and 131.7 to 134.3 in 2014, with 2008 as the baseline (StatsSA (n.d.)). Data from three households were identified as outliers and removed from the dataset.

We construct two saving measures. The first measure (version 1) is simply income minus consumption. This measure is likely to underestimate saving since durable consumption includes some elements of saving. In the second measure (version 2), we exclude durable consumption, which comprises of items such as household maintenance, furniture, and clothing. Hence the saving measure is income, minus expenditure, plus durable consumption.

Table 2: Descriptive statistics

Variable	Obs.	Mean	S.D.	Min	Max
Outcome variables					
Income	29,750	3,756	9,155	1	440,529
Consumption	31,467	2,716	7,562	3	589,749
Durable consumption	8,949	1,580	5,963	1	308,884
Non-durable consumption	31,062	1,994	3,820	3	377,114
Saving (version 1)	29,622	1,008	9,560	-549,749	426,167
Saving (version 2)	29,622	1,466	9,244	-549,749	429,515
Permanent income factors					
Assets (in deciles)	16,362	5.5	2.9	1	10
Under 5yo	31,627	0.5	0.8	0	13
6-11yo, male	31,627	0.3	0.6	0	5
6-11yo, female	31,627	0.3	0.4	0	6
12-17yo, male	31,627	0.2	0.5	0	5
12-17yo, female	31,627	0.3	0.5	0	5
18-64yo, male, $<$ 7 yrs edu.	31,627	0.1	0.4	0	6
18-64yo, female, $<$ 7 yrs edu.	31,627	0.2	0.5	0	5
18-64yo, male, 7-9 yrs edu.	31,627	0.4	0.6	0	7
18-64yo, female, 7-9 yrs edu.	31,627	0.2	0.5	0	7
18-64yo, male, $>$9 yrs edu.	31,627	0.2	0.5	0	6
18-64yo, female, $>$9 yrs edu.	31,627	0.6	0.8	0	7
$>$65yo, male	31,627	0.1	0.3	0	3
$>$65yo, female	31,627	0.1	0.4	0	3
Transitory income factors					

Rainfall, deviation from mean (mm)					
Planting season	31,245	11.5	60.8	-98.8	219.3
Growing season	31,245	-2.2	69.3	-155.5	198.2
Rest of year	31,245	-32.2	60.8	-167.9	156.3
Rainfall, coefficient of variation (σ/μ)					
Planting season	31,245	2.1	0.7	1.2	6.2
Growing season	31,245	2.0	0.7	1.2	5.3
Rest of year	31,245	3.7	1.2	1.7	8.5
Temperature, deviation from mean (deg)					
Planting season	31,245	-0.1	1.0	-2.8	3.3
Growing season	31,245	0.2	1.2	-3.5	2.9
Rest of year	31,245	0.5	0.7	-1.9	2.5
Temperature, coefficient of variation (σ/μ)					
Planting season	31,245	0.1	0.03	0.08	0.2
Growing season	31,245	0.1	0.03	0.04	0.2
Rest of year	31,245	0.2	0.06	0.08	0.4
Days in growing season over 34 deg C	31,245	36	27	0	88

Note: For saving, negative values refer to dissaving in last 30 days, according to survey output. I opt to retain in order to have minimum interference with raw data. For weather variables, in South Africa, planting season refers to October to December of previous year, growing season refers to January to March, and rest of the year refers to April to September.

We also assess the distributional effect on propensity to save. The gross domestic savings (as % of GDP) in South Africa in this period ranges from 21.5 in 2008 to 19.1 in 2014 (WorldBank (n.d.-a)). In our sample, the average saving rate is 27% when durable goods are considered consumption which is higher than the aggregate number reported by the World Bank. We provide the summary statistics on the outcome variables by income quartile is presented in Table 3.

Table 3: Summary of income and saving by quintile

Income quintiles	Income (SFR)	Saving (v.1) (SFR)	(% of inc.)	Saving (v.2) (SFR)	(% of inc.)
Lowest 20%	581	-387	-66%	-255	-44%
20% to 40%	1,153	35	3%	138	12%
40% to 60%	1,860	283	15%	489	26%
60% to 80%	3,124	837	27%	1,149	37%
Highest 20%	12,096	4,281	35%	5,819	48%

5. Empirical approach

Starting with Equation 8, we make a slight modification by including time heterogeneity in the variance term. The empiric equation is

$$S_{irt} = \alpha_0 + \alpha_1 Y^P_{irt} + \alpha_2 Y^T_{irt} + \alpha_3 \text{VAR}_{irt} + \alpha_4 W_{irt} + \epsilon_{irt} \tag{9}$$

As presented in the theoretical framework, the standard model would predict that α_1 should be close to zero, while α_2 should be close to one in the case of certainty equivalence. In the case of a buffer stock model, α_1 should be greater than zero. The estimated α_3 is a measure of risk aversion and should be greater than zero without certainty equivalence.

Following Paxson (Paxson (1992)), we estimate permanent income as

$$Y^P_{irt} = \beta^P_{ir} + \beta_1 X^P_{irt} + u^P_{irt} \tag{10}$$

where X^P_{irt} includes a set of variables that capture the households assets and demographic characteristics. We use market value of the dwelling (owned houses) as an indication of the asset level of the household. If the household rents, then the asset level is zero. Otherwise, asset level is categorized into deciles in order to reduce potential measurement error in the explanatory variables. Furthermore, we construct household demographic structure by categorizing household members by age, gender and education levels. The demographic structure of the households is divided into 13 categories, as described in Appendix 8.3. β^P_{ir} captures household fixed effects, and u^P_{irt} is the stochastic error term.

We estimate transitory income using temperature and precipitation. These weather variables are likely correlated, and including one without the other may lead to omitted variable problems

(Auffhammer, Hsiang, Schlenker, and Sobel (2013)). We estimate the following linear expression for transitory income.

$$Y^T_{irt} = \beta^T_t + \beta_2 X^T_{irt} + u^T_{irt} \tag{11}$$

where X^T_{irt} represent a set of parameters that characterize temperature, rainfall and extreme degree-days. Presumably, some portions of the transitory income are not incorporated in this specification (e.g., periods of reduced working hours or job loss), and are absorbed in the error term. β^T_t is year fixed effects to capture the year-to-year variation in transitory income not captured by weather, and u^T_{irt} is the error term.

Given the expressions of permanent and transitory income, total income can be expressed as the sum of the two:

$$Y_{irt} = \beta^T_t + \beta^P_{ir} + \beta_1 X^P_{irt} + \beta_2 X^T_{irt} + u_{irt} \tag{12}$$

The saving equation can therefore be expressed as:

$$S_{irt} = \alpha_0 + \alpha_1(\beta^P_{ir} + \beta_1 X^P_{irt} + u^P_{irt}) + \alpha_2(\beta^T_t + \beta_2 X^T_{irt} + u^T_{irt}) + \alpha_3 \mathrm{VAR}_{irt} + \alpha_4 W_{irt} + \epsilon_{irt} \tag{13}$$

After simplification, the saving equation becomes:

$$S_{irt} = \gamma_t + \gamma_{ir} + \gamma_1 X^P_{irt} + \gamma_2 X^T_{irt} + \gamma_3 \mathrm{VAR}_{irt} + v_{irt} \tag{14}$$

where γ_t is time fixed effects, $\alpha_2\beta^T_t$, γ_{ir} is the constant α_0 and household fixed effects $\alpha_1\beta^P_{ir}$, γ_1 is $\alpha_1\beta_1$, γ_2 is $\alpha_2\beta_2$, and γ_3 is α_3. W_{irt} does not appear in the reduced form equation as it is collinear with determinants of permanent income.

We first undertake the regression of saving equation as specified in Equation 14. We test the joint significance of permanent and transitory factors on saving (i.e., γ_1 and γ_2.) If the permanent income hypothesis holds, then we should see that γ_1 is not significantly different from zero, while γ_2 is significantly different. By contrast, the buffer stock model would predict that γ_1 is different from zero. The coefficient γ_3 represents the significance of risk measure in the saving equation.

Next, we undertake a procedure to estimate the propensities to save out of permanent and transitory income (i.e., α_1, α_2 from Equations 9 and 13). In the first step, we regress permanent and transitory factors on income as specified in Equation 13. We use the estimated coefficients to construct permanent income ($\hat{Y^P_{irt}}$), and transitory income ($\hat{Y^T_{irt}}$). In the second step, we estimate the saving equation using the fitted values.

$$S_{irt} = \alpha_1 \hat{Y^P_{irt}} + \alpha_2 \hat{Y^T_{irt}} + \alpha_3 \text{VAR}_{irt} + \alpha_4 W_{irt} + \alpha_5 \hat{u_{irt}} + w_{ir} + v_t + \epsilon_{irt} \tag{15}$$

We include the residual from the income regression, $\hat{u_{irt}}$, in the estimation of the saving equation, as income residual is often interpreted as transitory component of the income (Paxson (1992)). For household life-cycle factors (W_{irt}), we use the categories of demographic factors presented in Table 1, Table 2 and in Appendix 8.3.

We test the joint significance of coefficient for income variance (α_3) in the saving equation (Equation 15). Income variance is represented by coefficient of variation of the weather variables. If we assume that the underlying utility function is isoelastic, we expect that this coefficient is significantly different from zero.

We compare the result of the OLS regression in the second stage with results of a median regression. Linear regression summarize the average relationship between a set of regressors and the outcome variable based on the conditional mean function $E(y|x)$. Median regression, or least absolute deviation (LAD) regression, consider the relationship using the conditional median function $Q_{50}(y|x)$. If ϵ_i is the model prediction error, OLS minimizes $\sum_i e_i^2$ while median regression minimizes $\sum_i |e_i|$. It minimizes a sum that gives asymmetric penalties $0.5|e_i|$ for overprediction and $0.5|e_i|$ for underprediction. While OLS can be inefficient if the errors are highly non-normal, median regressions are more robust to non-normal errors and outliers (Wooldridge (2012)).

To assess the distributional effects on the propensity to save, we divide income into quintiles, and assess the result of median regressions by each quintile. We construct dummy variables for each quintile, and allow the estimate of the median regression to vary with each quintile, while the constant remains the same. This is similar to the methodology used by Dynan (Dynan et al. (2004)) using data from US Survey of Consumer Finances in their investigation of the relationship between saving rate and current income. We report the result from the full set of income and saving data, using both saving (v.1) and saving (v.2), which investigates the role of durable goods as a saving mechanism.

In the next section, we report the main findings of our empirical study.

6. Results

6.1 Propensity to save with OLS and median regressions

Table 4 presents the results of the joint significance tests from Equations 12 and 14. Standard errors are clustered at districts, which is aggregation level of weather data. We present results from three sets of tests. The first one is the regression of permanent and transitory income factors on income, following Equation 12. The next two are the regression of permanent and transitory income factors on saving (version 1 and version 2), following Equation 14.

As predicted from previous studies (Paxson (1992)), we find significant effect of asset, demographic, and weather variables on income, suggesting that the underlying factors that drive permanent income (e.g., assets and demographics) and transitory income (e.g., weather) are predictors of household income. From the standard model, we would expect to find the coefficients of permanent income on saving to be non-significant, and transitory income on saving to be significant. In this sample, we find that the coefficients on transitory income is significant. We find that the coefficients of permanent income on saving is significant when durable consumption is excluded as saving, but not significant when durable consumption is included. In addition, the coefficients on income variance is not significant when durable goods are not considered as saving, and weakly significant when durable goods are considered as saving.

Table 4: Test of joint significance on income and saving

F-statistic	Income	Saving (v.1)	Saving (v.2)
Permanent income (X^P_{irt})	3.35***	2.51**	1.53
Transitory income (X^T_{irt})	2.28*	4.52***	4.62***
Income variance (VAR_{irt})	-	1.68	1.99*
Controls			
Household fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes
Observations	15,588	15,559	15,559

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. Standard errors clustered at districts.

Using permanent and transitory income factors, we construct estimated permanent and transitory income, $\hat{Y}^P_{irt}$ and $\hat{Y}^T_{irt}$. Table 5 outlines the second stage result of the regression from Equation 15. We first use a pooled OLS model for the second stage regression. We find that $\hat{\sigma}(u_i) = 0$, which indicates that the standard deviation of the individual effects is zero. In this case, the GLS is equivalent to OLS and there is no heterogeneity in individual fixed effect.

For every unit increase in estimated transitory income, saving (v.1) increases by 0.77 units. For every unit increase in estimated permanent income, saving (v.1) increased by 0.71 units. There is no significant differences between the coefficients of permanent income and transitory income. However, while we can strongly reject that hypothesis that the coefficient on permanent income is equal to one, we can weakly reject this hypothesis for transitory income. When durable goods are considered as saving, we cannot reject the hypothesis that the marginal saving out of transitory income is equal to one. While the propensity to save from permanent income is not zero, it is also not close to one. Some portion of permanent income is also saved. This result is in alignment with result from Paxson (Paxson (1992)) (although the marginal saving on permanent income is higher than that found in Paxson's study).

The residual from the OLS regression has a non-normal distribution. While the mean is close to zero, it is not symmetrically distributed around the mean. Normality test (Shapiro-Francia and Kolmogorov-Smirnov) rejects the null hypothesis that the residual is normally distributed.

We also present the results of median regression in Table 5. The difference between the marginal saving from OLS versus median regression reflect the difference between the estimator of the expected conditional mean and the expected conditional median. Since the residual from OLS is not normally distributed, median regression using least absolute deviation is more robust to outliers.

Estimated marginal saving using median regression is smaller in magnitude than OLS. We reject both null hypotheses that the marginal saving from permanent and transitory saving is equal to one.

Table 5: Estimated propensity to save

	OLS		Median	
Coefficients	Saving (v.1)	Saving (v.2)	Saving (v.1)	Saving (v.2)
Permanent income ($\hat{Y}^P_{irt}$)	0.71***	0.77***	0.52***	0.64***
Transitory income ($\hat{Y}^T_{irt}$)	0.77***	0.90***	0.55***	0.59***
Residual ($\hat{u}^T_{irt}$)	0.93***	0.99***	0.67***	0.81***
Controls				
Household fixed effects	No	No	No	No
Year fixed effects	Yes	Yes	Yes	Yes
Household demographic	Yes	Yes	Yes	Yes
Income variation	Yes	Yes	Yes	Yes
Test statistics				
$\hat{Y}^P_{irt} = \hat{Y}^T_{irt}$	0.24	1.56	4.21*	0.50
$\hat{Y}^P_{irt} = 1$	33.99***	32.49***	889***	271***
$\hat{Y}^T_{irt} = 1$	5.37*	1.31	377***	25***
$VAR_{irt} = 0$	6.36***	7.26***	5.95***	3.07***
R^2 overall	0.44	0.56	0.43	0.55
No. of observations	15,559	15,559	15,559	15,559
Distribution of residuals				
Mean	4.83E-7	3.82E-7	-	-
Std. Dev.	9,142	7,811	-	-
Shapiro-Francia	$p < 0.001$	$p < 0.001$	-	-
Kolmogorov-Smirnov	$p < 0.001$	$p < 0.001$	-	-

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. Standard errors clustered at districts. Shapiro-Francia and Kolmogorov-Smirnov are normality tests which assess whether the residual from the OLS regression follow a normal distribution.

6.2 Propensity to save by income deciles

We present the propensity to save by income deciles in two subsections. In the first subsection, we include the full data set and evaluate the result using saving v.1 where durable goods is considered as part of consumption. In the second subsection, we evaluate the results using saving v.2, where durable goods is considered as part of saving.

6.2.1. Durable goods as consumption

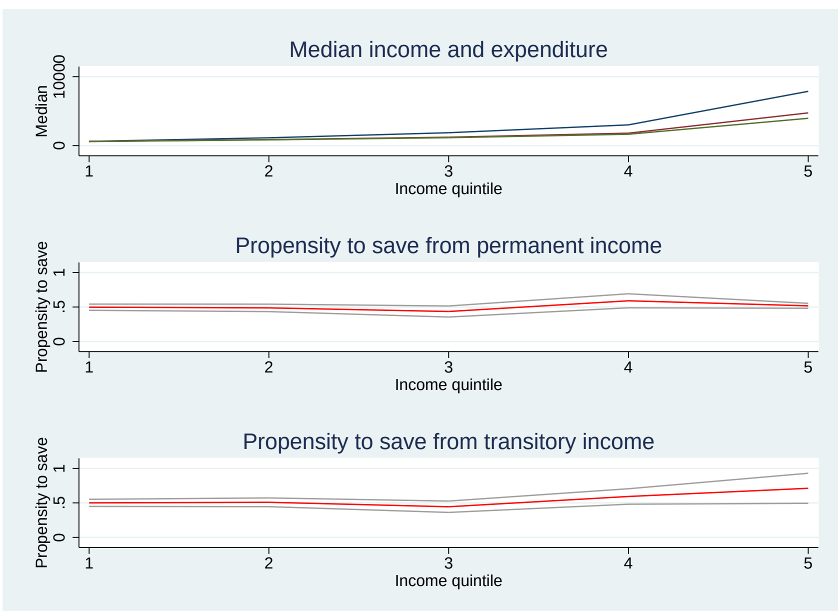
Table 6 presents the result of median regressions of saving (v.1) by income quintiles, and Figure 1 presents the results graphically. When durable goods are considered as consumption, saving is total income subtracting total expenditure including durable goods. With this outcome specification, we find no difference in marginal saving rate across income quintile. While there is a slight trend towards higher marginal saving for the highest 20% of the income distribution, we cannot reject the null hypothesis that it is the same as the lowest 20%.

Table 6: Estimated propensity to save by income quintiles

	Income quintiles				
Coefficients	20%	40%	60%	80%	100%
Permanent income ($\hat{Y}_{irt}^{P}$)	0.50***	0.49***	0.44***	0.59***	0.52***
Transitory income ($\hat{Y}_{irt}^{T}$)	0.50***	0.51***	0.44***	0.59***	0.71***
Residual ($\hat{u}_{irt}^{T}$)	0.54***	0.51***	0.52***	0.75***	0.79***
Controls					
Household fixed effects	No	No	No	No	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Household demographics	Yes	Yes	Yes	Yes	Yes
Income variation	Yes	Yes	Yes	Yes	Yes
Test statistics					
$\hat{Y}_{irt}^{P} = \hat{Y}_{irt}^{T}$	0.04	2.28	0.26	0.00	2.92
$\hat{Y}_{irt}^{P} = 1$	477***	346***	190***	62***	695***
$\hat{Y}_{irt}^{T} = 1$	358***	230***	175***	51***	7**
$\hat{Y}_{irt}^{P}$ of bottom 20% = top 20%			0.38		
$\hat{Y}_{irt}^{T}$ of bottom 20% = top 20%			2.95		

*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. Standard error clustered at districts.

Figure 1: Propensity to save by quantiles, full data set



Note: Top graph panel represent median income and expenditure (total and non-durable expenditure). Red lines in graph panels below represent median regression estimates. Gray lines represent 95% confidence intervals.

6.2.2. Durable goods as saving

Table 7 presents the result of median regressions of saving (v.2) by income quintiles, and Figure 2 presents the results graphically. In this case, the outcome variable, saving, include durable consumption of the period. Consumption in this period include non-durable consumption and housing. If we consider the purchase of a durable good as a saving mechanism, then we would consider this measure of saving as a more accurate reflection of saving. In this case, we reject the null hypothesis that the marginal saving of the poorest 20% is the same as the richest 20% for both permanent and transitory income. There is an increasing trend in marginal saving for both permanent income and transitory income. In addition, for the top 20% of income distribution, the marginal saving from transitory income is significantly different from the marginal saving from permanent income, although both are different from one.

Table 7: Estimated propensity to save by income quintiles

	Income quintiles				
Coefficients	20%	40%	60%	80%	100%
Permanent income ($\hat{Y}^P_{irt}$)	0.56***	0.56***	0.51***	0.66***	0.64***
Transitory income ($\hat{Y}^T_{irt}$)	0.57***	0.58***	0.53***	0.67***	0.80***
Residual ($\hat{u}^T_{irt}$)	0.59***	0.58***	0.59***	0.75***	0.88***
Controls					
Household fixed effects	No	No	No	No	No
Year fixed effects	Yes	Yes	Yes	Yes	Yes
Household demographics	Yes	Yes	Yes	Yes	Yes
Income variation	Yes	Yes	Yes	Yes	Yes
Test statistics					
$\hat{Y}^P_{irt} = \hat{Y}^T_{irt}$	1.50	2.59	1.38	0.09	10.13**
$\hat{Y}^P_{irt} = 1$	553***	358***	192***	75***	557***
$\hat{Y}^T_{irt} = 1$	349***	209***	159***	44***	15***
$\hat{Y}^P_{irt}$ of bottom 20% = top 20%			8.76**		
$\hat{Y}^T_{irt}$ of bottom 20% = top 20%			12.29***		

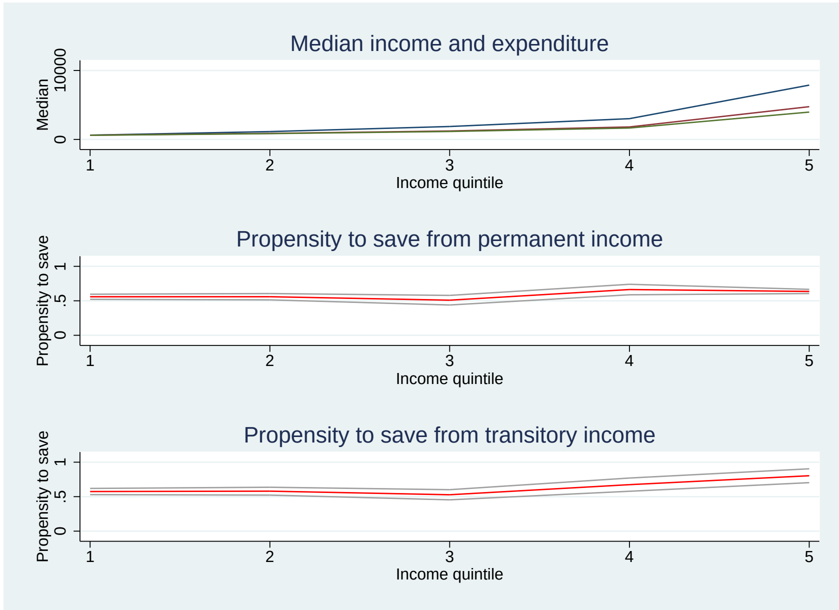
*** $p < 0.001$ ** $p < 0.01$ * $p < 0.05$. Standard error clustered at districts.

7. Conclusion

We conduct a decomposition of income into permanent and transitory income, using a newly available, detailed household panel dataset from South Africa. We evaluate the propensity to save on income, using a set of factors to proxy for permanent and transitory income. For permanent income, we use household demographic categories and household asset level. For transitory income, we use district-level rainfall and temperature data adjusted for agricultural seasons. We include both deviation from long term climate norms, and coefficient of deviation of the weather data. We test the permanent income hypothesis, which states that the propensity to save from permanent income should be close to unity, while the propensity to save from transitory income should be close to zero. We also test the propensity to save by income quintiles in order to identify any differences in saving behavior among income categories.

Following Paxson (Paxson (1992)), we find a significant effect of transitory income as proxied

Figure 2: Propensity to save by quantiles, full data set



Note: Top graph panel represent median income and expenditure (total and non-durable expenditure). Red lines in graph panels below represent median regression estimates. Gray lines represent 95% confidence intervals.

by weather variables, on household saving, in a reduced form fixed effect framework. In our two-step analysis, an OLS framework in the second step yield a propensity to save on permanent income of 0.71, and a propensity to save on transitory income of 0.77. While the propensity to save on permanent income is significantly rejected from unity, the null cannot be rejected for the propensity to save from transitory income. This confirms the predictions of the permanent income hypothesis that propensity to save from transitory income is close to unity. Similar to the finding by Paxson (Paxson (1992)), however, some portion of permanent income is also saved.

We proceed to conduct a series of median regressions, in order to account for potential outliers due to distribution of our income and saving variables. The median propensity to save from permanent income and transitory income are on the order of 0.51 and 0.52. The null hypothesis that either propensities to save is unity is now strongly rejected.

We conduct a series of analysis on the median propensity to save by income quintiles, in order to examine differences in saving behavior at lower end and higher end of the income distribution. We consider two cases. One case is when durable consumption is considered as part of consumption, and thus not included in saving. In this case, we find that the propensity to save is not significantly different between the bottom 20% and top 20% of the income distribution. When we include durable consumption as part of saving, we find that the propensity to save from transitory income significantly differs from permanent income. There is a trend of increasing saving with transitory income, however, we still reject the hypothesis that the propensity to save from transitory income is close to unity for the highest quintile.

Overall, our findings seem to suggest that households save from both permanent income and transitory income. There is a difference in the scale of saving between an OLS and a median analysis. The distribution of our income and saving data seem to point to median regression as a more appropriate model, where the propensity to save is estimated at around 0.50 from both permanent and transitory income. When we account for the distributional differences in income, we find that the account of durable goods makes a difference in the resulting propensities to save. When durable goods are considered as consumption, there is no difference in propensities to save between the bottom 20% and top 20% of the distribution. However, when durable goods are considered as saving, there is a significant difference between the propensity to save between the bottom 20% and top 20%. In addition, there is a trend of increasing saving on transitory income, although we still reject the null hypothesis that the propensity to save on transitory income is close to unity even in the highest quintile.

8. Appendices

8.1 Summary figures on weather variables

Figure 3: Cumulative distribution of temperature (1980-1989 and 2010-2015, unit: deg K)

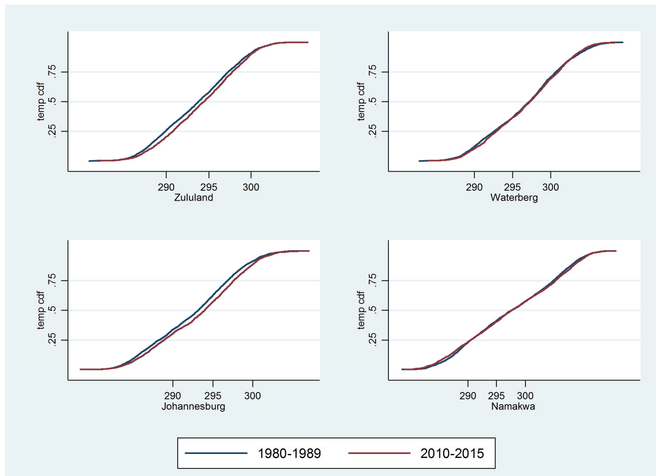
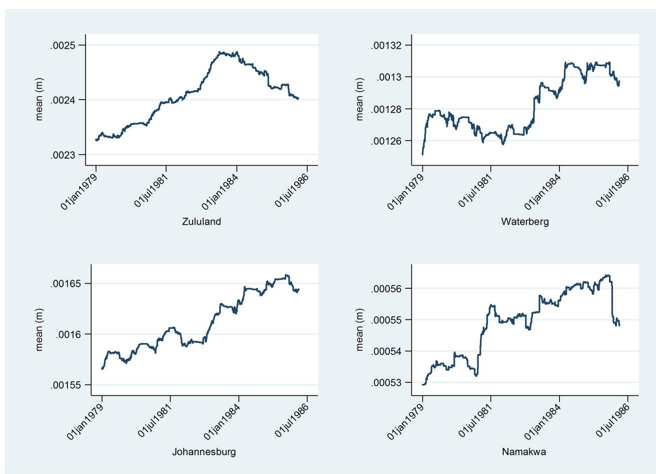


Figure 4: Mean daily precipitation (rolling 30-years, unit: m)



8.2 Household panel data collection summary

In the first stage, 400 primary sampling units (PSUs) were selected from Stats SAs Master Sample of 3,000 PSUs. This master sample is used for its Labour Force Survey and General Household Survey between 2004 and 2007, and for the Income and Expenditure Survey in 2005-2006. The target population includes private households in all nine provinces of South Africa and residents in workers hostels, convents and monasteries. The frame excluded students hostels, old age homes, hospitals, prisons and military barracks. The sample was proportionally allocated to strata based on master sample district council PSU allocations, and was not designed to be representative at the province level. Within each PSU, non-overlapping samples (clusters) of dwelling units were systematically drawn. This distribution of PSU clusters for NIDS is comparable to the Master Sample. An initial sample of 9,600 dwelling were drawn. In phase 1 of baseline collection, 6,498 households were successfully interviewed. Since the target response rate of 83% was not achieved, phase 2 data collection was undertaken. A 43% response rate was achieved in phase 2, resulting in an additional 807 successful households. Therefore, a total of 7,305 households were successfully interviewed in 2008 for the baseline, consisting of 28,255 individuals (Leibbrandt et al. (2009)). Two sets of weights were calculated for the sample. The design weights were calculated as the inverse of the probability of inclusion, and the post-stratification weights adjust the age-sex-race marginal total in the NIDS data to match the population estimates produced by Stats SA for mid-year population estimates for 2008. Constraints were imposed so that population distribution by province corresponds to population estimates and total weights add up to estimated population of 48,687,000. The in-field call-backs revealed that upper income households were reluctant to participate due to concerns of privacy and questions about the legitimacy of the study. Poorer households were more willing to participate because of availability (e.g., unemployment) and experience with similar previous community studies.

8.3 Demographic categories

Category	Age	Gender	Education
1	less than 5yo		
2	6 to 11 yo	male	
3	6 to 11 yo	female	
4	12 to 17 yo	male	
5	12 to 17 yo	female	
6	18 to 64 yo	male	less than 7 years
7	18 to 64 yo	male	7 to 9 years
8	18 to 64 yo	male	greater than 9 years
9	18 to 64 yo	female	less than 7 years
10	18 to 64 yo	female	7 to 9 years
11	18 to 64 yo	female	greater than 9 years
12	greater than 65 yo	male	
13	greater than 65 yo	female	

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