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WEATHER AND INCOME : EFFECT ON HOUSEHOLD SAVING AND WELL-BEING IN SOUTH AFRICA

Helena TING, Martina BOZZOLA, Timothy SWANSON

Weather and income: effect on household saving and well-being in South Africa

Ting, Helena[1]; Bozzola, Martina[2]; Swanson, Timothy[3]

[1] Corresponding author. Centre for International Environmental Studies, IHEID, Chemin Eugène-Rigot 2, 1202 Geneva. helena.ting@graduateinstitute.ch

[2] AECP Group, ETH Zurich, CH.

[3] Graduate Institute of International and Development Studies, Geneva.

Abstract

In countries where rain-fed agriculture constitutes a significant portion of household livelihood, increased weather variability represents a source of vulnerability to stable consumption, food security and household well-being. Weather induced income changes affect household consumption and saving decisions. We evaluate saving and consumption responses to weather variation in South Africa, leveraging a newly available panel of nationally representative households covering the period from 2008 to 2014 and long term climate data. We test our data against predictions of the standard rational consumption model and some of its main extensions (i.e., precautionary saving and myopic consumption), and compare differences among households engaged in agriculture activities versus those that do not. Furthermore, we evaluate the impact of saving on household life satisfaction and health behavior. In accordance with previous literature, we find that households save in response to both transitory and permanent income change, although the proportion saved from transitory income is significantly higher. We find signs of precautionary saving driven by non-agriculture households, while we find stronger evidences of myopic consumption for agriculture households. In addition, we show that a one-unit increase in log-saving from transitory income increases the odds of a unit increase in self-reported life satisfaction of the household head by 14%, and a one unit increase in log-saving from permanent income leads to a 6% increase in hazard ratio of having taken an HIV test. This latter result may indicate that preventative health behavior such as HIV testing requires a stronger inducement than a transitory injection of income. Further research is needed to identify the mechanisms by which saving affect life satisfaction and health seeking behavior in developing countries.

Key words: consumption and saving; health behavior; agriculture; climate; Africa; South Africa

JEL codes: D14; I14; Q12 ; Q56

Highlights

- Seasonal weather variability used to estimate transitory income.
- Significantly higher saving from transitory income than permanent income.
- Non-agriculture households show precautionary saving.
- Agriculture households show myopic consumption and saving from transitory income.
- Transitory income related saving is associated with increase in life satisfaction while permanent income related saving is associated with health seeking behavior (increase in HIV testing).

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1. Introduction

Consequences of climate change will disproportionately affect less developed parts of the world (IPCC, 2014). In South Africa, future warming in the range of 1-3°C and increasing rainfall variability is a threat to household livelihood, particularly for those that depend on rainfall for agriculture production (DEA, 2011; Ziervogel et al., 2014). Weather induced income changes affect households' consumption and saving decisions, and their coping strategies. While a wealth of evidence exists in developed countries on consumption response to income shocks, there is relatively less evidence based on comprehensive panel data in developing countries.

In this paper, we investigate if and how weather affects households' income and saving behaviors, distinguishing among agriculture and non-agriculture households in South Africa. We further examine the effect of saving behavior on well-being, as measured by self-reported life satisfaction, and on health behavior, captured through information on HIV testing. For this purpose, we compile a dataset of nationally representative households from South Africa for the period 2008 to 2014 based on its National Income Dynamic Study (NIDS, 2008, 2010, 2012, 2014), together with daily data on key climatic variables (e.g., temperature and precipitation) from European Centre for Medium-Range Weather Forecasts' ERA-Interim dataset (Dee, 2011).

Our study is related to consumption and saving responses to income change as put forth in the classic permanent income hypothesis (Modigliani and Brumberg, 1954; Friedman, 1957; Jappelli and Pistaferri, 2010). We start by decomposing permanent and transitory income based on exogenous factors and weather variability (Paxson, 1992), and proceed to examine household propensities to save. We then evaluate extensions of the theory by testing for evidence of precautionary saving and myopic consumption.[1] We analyze separately agriculture and non-agriculture households and compared the consequences of households' saving on self-reported life satisfaction and HIV testing. The latter has important implications in a country which has the largest and most high profile HIV epidemic in the world, with an HIV prevalence of about 19% among adults aged 15 to 49, although it varies markedly between regions (UNAIDS, 2015).

Consumption response to income changes has been studied in various ways, mostly in developed countries. Jappelli and Pistaferri (2010) provide a thorough review of the theory and evidence on this topic. Following full theoretical development, (e.g., Altonji and Siow, 1987; Zeldes, 1989; Shea, 1995), empirical findings have converged on some consensus that consumption responds to an anticipated income increase beyond what the theory would predict, which may be attributed to liquidity or credit constraints. Furthermore, consumption responses to permanent shocks are higher than transitory shocks, suggesting that precautionary saving might play a role in consumption (Blundell, Pistaferri, and Preston, 2008).

There have been few studies of consumption and saving behavior in developing countries, although such studies are particular relevant as these countries are often characterized by income fluctuations. Wolpin (1982) investigated permanent income elasticity of consumption in a panel of Indian farm households and found it to be close to unity, confirming the original permanent income hypothesis. 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. Gertler and Gruber (2002) studied the impact of illness on consumption in Indonesian village households and saw evidence of smoothing for minor illnesses, but less smoothing for major illnesses. Using Old Age Pension and Child Support Grant data from South Africa, Berg (2013) tested discontinuities in expenditure for evidence of credit constraint, myopic consumption and precautionary saving and suggest that credit constraint, rather than myopic consumption or precautionary saving, may explain the excess sensitivity of consumption to anticipated income changes. In this paper, we evaluate saving responses to household income changes as consequences of unpredictable changes in weather, and test for presence of precautionary saving and myopic consumption.

In countries like South Africa, where rain-fed agriculture still represent a significant portion of household livelihood, increased weather variability represent a particular source of vulnerability to stable consumption, food security and household wellbeing (Bryan and Deressa, 2009; Karfakis, 2012). Weather variability affects particularly farmers engaged in rain-fed crop production, which is predominant in many African countries (Bozzola, Smale, and Di Falco, 2016; Hirvonen, 2016; Kurukulasuriya and Mendelsohn, 2008). Persistent draughts, increased variability in rainfall and extreme temperatures may further exacerbate the ability of agricultural households to plan their agricultural activities. In turn, unpredictability in farming output translates into reduced ability of the household to smooth consumption. 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 (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. Through its indirect effects on food market prices, increasing weather variability may also negatively affect household consumption in non-agricultural households through increased uncertainty in food prices (Wheeler and von Braun, 2013).

Although there is an extensive literature on the relationship between income and subjective well-being[2], the evidence between saving and well-being is scarcer. Using data respectively from the Orang Asli in Malaysia and German Socio-Economic Panel, Howell (2006) and Obucina (2013) reported that saving increases life satisfaction levels. Using data on Turkish households, Gokdemir (2015) reported that a statistically significant relationship exist between spending on durable goods, which has a component of saving, and life satisfaction.[3] Furthermore, results from a field experiment in Kenya showed that when saving technologies are available, households rapidly took up the opportunity to save. Earmarking saving for health investment, however, was more effective in “emergency” settings rather than “preventative” settings, as the saved funds were seen as most effective as a tool to reduce “unplanned expenditures” (Dupas and Robinson, 2013).

We follow Wolpin (1982) and Paxson (1992) by using weather variability as a predictor for transitory income. Our weather variables incorporate seasonal differences and variances in temperature and rainfall from climate normals[4] and extreme temperature degree-days (Dell, 2014; Hirvonen, 2016; Hsiang, 2016). We test for alignment of household behavior with standard consumption models and its extensions, similar to Paxson (1992) and Berg (2013). Furthermore, we evaluate the relationship between saving and life satisfaction using a conditional ordered logit methodology, as outlined in Baetschmann (2015), and the relationship between saving and HIV testing using a hazard ratio analysis that takes into consideration number of events that occur within a time period.

We make three main contributions to existing literature. First, we provide evidence of household saving and consumption behavior in a developing country that is strongly affected by weather variability. We do this by compiling a unique dataset of household level information with detailed weather and climate information, and testing alignment of household behavior with rational consumption model and extensions (i.e., precautionary saving and myopic consumption). Second, we identify differences in saving and consumption behavior between agricultural and non-agricultural households. In this we contribute to the literature looking at the often-neglected commonalities and differences between rural and urban poverty, and their implications for policy interventions (Rakodi and Lloyd-Jones, 2002). Third, we evaluate the welfare impact of such behavioral differences by looking at self-reported life satisfaction, and health behavior in the case of undertaking an HIV test.

Our analysis reveals saving and consumption behavior that confirms many insights of the standard model, but with some interesting deviations. While the standard model predicts that the propensity to save from transitory income should be close to unity while that of permanent income should be close to zero, we find that saving from both transitory and permanent income are significant. However, the proportion saved from transitory income is significantly higher than permanent income, which indicates that households save proportionally more from transitory income. We find signs of precautionary saving in our sample households, driven primarily by non-agriculture households, while agriculture household generate more income from transitory sources, and have a positive saving response to only increases in transitory income. In our analysis, myopic consumption cannot be rejected when non-durable goods are considered, and this effect is stronger for agriculture households. On self-reported life satisfaction, we conclude that a one-unit increase in log-saving from transitory income significantly increases the odds of a one-step increase in life satisfaction by 14%. This result is consistent across agriculture and non-agriculture households, and is robust to household life-cycle factors and income variance. Furthermore, we find a 5% to 6% increase in the incidence hazard ratio of HIV testing with a one-unit increase in log-saving from permanent income. This is also significant across agriculture and non-agriculture households, and consistent when we measure the ratio across individuals, or at the household level.

The paper proceeds as follows: in Section 2 we outline a theoretical model of consumption response to income changes and present a testable empirical specification. In Section 3, we detail our sources of data, present descriptive statistics, and outline the empirical approach. We present our results in Section 4, and conclude in Section 5.

2. Theoretical Model

In this section, we present the theoretical model of rational consumption response to income changes for a representative household. We follow the model presented in Jappelli and Pistaferri (2010), and highlight how this applies to our context.

We 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 $y_{it} = \overline{y_{it}} + \varepsilon_{it}$, where $\overline{y_{it}}$ is deterministic and ε_{it} represent shocks with $E(\varepsilon_{it}) = 0$. The agent chooses consumption c_{it} to maximize remaining lifetime expected utility $E_{it} \sum_{\tau=t}^{\infty} \delta^{\tau-t} u(c_{i\tau})$, subject to the budget constraint $w_{i\tau} = (1 + r_\tau)w_{i,\tau-1} + y_{i\tau} - c_{i\tau}$ and $w_{i\tau} \geq \underline{w_{i\tau}}$ where w_τ is wealth in period τ, and y_τ is income in period τ. If the utility function is time-separable, then the Euler equation becomes:

$$u'(c_{it-1}) = (1 + \delta)^{-1} E_{t-1}[(1 + r_t)u'(c_{it})] \tag{1}$$

where *c* is consumption, δ is the discount rate, *r* is the real interest rate (Berg, 2013; Jappelli and Pistaferri, 2010). If the discount rate and interest rate are constants and equal to each other, then the Euler equation becomes:

$$E_{t-1}[u'(c_{it})] = u'(c_{it-1}) \tag{2}$$

As in the standard model, if we assume a quadratic utility function, we obtain the permanent income model with certainty equivalence (Campbell, 1987; Flavin, 1981; Jappelli and Pistaferri, 2010). We can write as the Euler equation as:

$$c_{it} = c_{i,t-1} + \varepsilon_{it} \tag{3}$$

where $\varepsilon_{it} = c_{it} - E_{t-1}c_{it}$ is the consumption modifier that depends on new information about uncertainties faced by the agent. Assuming labor income uncertainty in the future periods, we can further write changes in consumption from period *t-1* to *t* as:

$$\Delta c_{it} = \frac{r}{1+r}\sum_{t=0}^{\infty}(1+r)^{-\tau}(E_t - E_{t-1})y_{i,t+\tau} \tag{4}$$

where $r/(1+r)$ is the annuity factor under the assumption of infinite horizon. If we further assume that 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 we can write

$$\Delta c_{it} = \frac{r}{1+r}v_{it} + u_{it} \tag{5}$$

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 (1987), the saving equation can be written as

$$s_{it} = \frac{1}{1+r}v_{it} \tag{6}$$

This identity implies that saving should respond to changes in transitory income, such as weather-induced ones in our empirical model, but not permanent income (Jappelli and Pistaferri, 2010).

To incorporate precautionary saving, we assume that the utility function is isoelastic[5], so that the agent is risk-averse. 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 she approaches asymptotic utility faster with less consumption (Berg, 2013). Assuming consumption is log-normally distributed, the first order condition becomes:

$$\Delta lnc_{it} = \frac{\gamma}{2} var_{t-1}(\Delta lnc_{it}) + \varepsilon_{it} \tag{7}$$

where an additional risk component γ is introduced. γ represents the coefficient of relative risk aversion from the isoelastic utility function (Berg, 2013; Jappelli and Pistaferri, 2010).

Paxson (1992) specifies a testable form of the saving equation that is linear in permanent income, transitory income, and the variance of income. This is obtained after maximization of lifetime utility using a quadratic or constant absolute risk aversion (CARA) utility function. With the assumption that the household's income is normally distributed, the saving equation of the utility-maximizing agent can be written as:

$$S_{irt} = \alpha_o + \alpha_1 Y_{irt}^P + \alpha_2 Y_{irt}^T + \alpha_3 VAR_{ir} + \alpha_4 W_{irt} + \varepsilon_{irt} \tag{8}$$

Where S_{irt} is saving for individual *i*, in region *r*, at time *t*. Y_{irt}^P represents the permanent portion of the individual's income, while Y_{irt}^T 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 $\alpha_1$should be close to zero, while α_2 should be close to one. The prediction of α_3 should be close to 0 if a quadratic utility function is assumed as risks and 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.

We extend this model to a constant relative risk aversion (CRRA) utility function (e.g., isoelastic utility). This allows us to look at saving that is log-normally distributed, which is the case in our panel data (see Appendix E).

In the next Section we present the data, descriptive statistics and the empirical approach we adopt to test the relationships presented in this theoretical framework.

3. Empirical Approach

3.1. Data

We build a unique dataset with panel data for a nationally representative sample of South African households recorded during the period of 2008 to 2014 (NIDS, 2008, 2010, 2012, 2014), and link these data with weather and climate data covering mean daily temperature and daily total precipitation (Dee, 2011).

3.1.1. Household Data

The National Income Dynamic Study (NIDS) collects representative household consumption and income information in two-year increments, starting in 2008 (NIDS, 2008, 2010, 2012, 2014). The data is rich in individual and household characteristics, spending pattern, health and education, and well-being. This data has been used to study the evaluation of gender effects and food adequacy of subsistence farming in South Africa (Tibesigwa and Visser, 2016; Tibesigwa, Visser, and Turpie, 2015).

The NIDS follows a stratified, two-stage clustered sample design. Leibbrandt (2009) provides detailed description of the sampling and data collection methodology. We present a summary in Appendix A. 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.

3.1.2. Climate Data

We compile mean daily temperature and daily total precipitation data from the European Centre for Medium-Range Weather Forecasts' ERA-Interim dataset (Dee, 2011). This dataset provides a reanalysis of global atmosphere since 1979, on a 0.75-by-0.75 degrees resolution grid. 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, 2014; Colmer, 2016a, 2016b; Kudamatsu, 2014; Schlenker and Lobell, 2010) as it can be a valuable alternative when studying geographies where weather observation stations are scarce and scattered with inconsistent reporting (Berrisfold, 2011; Dee, 2011).

We link temperature and precipitation data to 52 districts in nine provinces of South Africa with corresponding GPS coordinates. We outline the matching methodology in Section 3.2.2. The districts range from the City of Johannesburg, with an area of 1,645 square kilometers, to Namakwa in Northern Cape, with an area of 126,836 square kilometers (Statistics South Africa, 2011).[6] We use over 30 years of climate data (temperature and precipitation, from 1979 to 2014) by district, which is the most granular level of geographic unit we can use to link climate variables with our household level information from NIDS.

3.2.Descriptive Statistics

Definition of key variables and descriptive statistics are provided in Table 1 and Table 2. Additional descriptive data is available in Appendices B and C. Mean income for South African households over the study period is 3,847 South African Rand (SFR), with a statistical difference between income for agriculture households (2,793 SFR) and non-agriculture households (4,195 SFR) ($p<0.001$) (see Table 2 and Appendix C). There exist significant differences between agriculture and non-agriculture households in terms of amenities (e.g., piped water, electricity) and demographic characteristics (e.g., number of children, percent of female household heads, etc.) (see Appendix B).

Table 1: Variables definition

Variable	Definition
Income, consumption and saving - unit: South African Rand. (Source: NIDS)	
Income	Total HH income from all sources in the previous 30 days
Durable consumption	Expenditure in HH maintenance, kitchen, furniture, clothing, etc. in previous 30 days
Consumption	Total consumption, including or excluding durable consumption, in the previous 30 days
Saving	Income minus consumption, including or excluding durable consumption, for previous 30 days
Permanent income predictors. (Source: NIDS)	
Assets (in quintiles)	Market value of owned house in quintiles (rent=0)
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	No of HH male/female members from 18 to 64 years

education	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 predictors – district-specific, seasonal climatic variables. (Source: ERA-Interim)

Rainfall, deviation from mean (mm)	Seasonal total rainfall deviation from climate normal
Rainfall, coefficient of variation (σ/μ)	Rainfall standard deviation divided by mean in the same season
Temperature, deviation from mean (mm)	Seasonal mean deviation from climate normal
Temperature, coefficient of variation	Temperature standard deviation divided by mean in the same season
Days in growing season over 34° C	No days in the growing season warmer than 34° C

Wellbeing and health indicators. (Source: NIDS)

Life satisfaction	Household Head's self-reported life satisfaction, on 1 (lowest self-reported life satisfaction) to 10 (highest self-reported life satisfaction) scale
HIV testing (household)	Indicator of whether any household had at least one individual over the age of 15 with HIV testing
HIV testing (individual)	Indicator of whether any individual over the age of 15 had HIV testing

Table 2: Descriptive statistics on key variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Income, consumption and saving (SAR)					
Income	20,803	3,847	10,693	0	541,924
Durable consumption	27,024	355	3,155	0	309,320
Consumption (including durable)	20,393	2,162	8,819	0	797,357
Saving (excluding durable)	19,338	1,768	12,702	-789,075	539,276
Consumption (excluding durable)	20,393	1,720	9,285	-305,793	795,885
Saving (including durable)	19,338	2,209	13,435	-787,603	539,519
Permanent income predictors					
Assets (in quintiles)	16,760	2.6	1.6	0	5
Under 5 yo	41,852	0.2	0.5	0	8
6-11yo, male	41,852	0.2	0.5	0	5
6-11yo, female	41,852	0.2	0.5	0	5
12-17yo, male	41,852	0.2	0.4	0	5
12-17yo, female	41,852	0.2	0.4	0	4
18-64yo, male, <7yrs of education	32,879	0.1	0.4	0	6
18-64yo, male, 7-9yrs of education	32,879	0.2	0.4	0	4
18-64yo, male, >9yrs of education	32,879	0.4	0.6	0	6
18-64yo, female, <7yrs of education	32,879	0.2	0.5	0	4
18-64yo, female, 7-9yrs of education	32,879	0.2	0.5	0	6
18-64yo, female, >9yrs of education	32,879	0.5	0.7	0	7
>65yo, male	32,879	0.1	0.3	0	2
>65yo, female	32,879	0.2	0.4	0	2
Transitory income predictors – weather					
Rainfall, deviation from mean (mm)					
Planting season	29,080	10.2	59.9	-98.8	219.3
Growing season	29,080	-2.2	66.6	-155.5	198.2
Rest of the year	29,080	-30.4	58.2	-167.9	156.3

Rainfall, coefficient of variation (σ/μ)					
Planting season	29,080	2.1	0.7	1.2	6.2
Growing season	29,080	1.9	0.7	1.2	5.3
Rest of the year	29,080	3.6	1.2	1.7	8.5
Temperature, deviation from mean (degree)					
Planting season	29,080	-0.1	1.0	-2.8	3.3
Growing season	29,080	0.2	1.2	-3.5	2.9
Rest of the year	29,080	0.5	0.7	-1.8	2.5
Temperature, coefficient of variation (σ/μ)					
Planting season	29,080	0.1	0.03	0.08	0.2
Growing season	29,080	0.1	0.03	0.04	0.2
Rest of the year	29,080	0.2	0.06	0.08	0.4
Days in growing season over 34° C	29,080	37	27	0	88
<u>*Wellbeing and health indicators*</u>					
Life satisfaction	162,153	5.1	2.4	1	10
HIV testing (household)	21,301	0.8	0.4	0	1
HIV testing (individual)	50,130	0.6	0.5	0	1

Note: In saving variables, negative values refer to more expenditure than income in the previous 30 days, according to survey output. In consumption excluding durable, negative values refer to more durable consumption than total consumption reported for the household. These deviations could be the result of measurement and recording errors from the survey process. We opt to retain these in our dataset, in order to have minimum interference with raw data. We incorporate two versions of saving and consumption variables. In one set, durable consumption is counted in consumption data, and excluded from saving data. For the other set, durable consumption is counted in saving, but not in consumption. For weather variables, 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.

3.2.1. Income, consumption and saving

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 member's salaries and wages, grants, interest, rental income and income from agriculture. Average "missingness" across all four waves of the survey is 20.5%, and is within the range of typical household surveys.[7] There is reported evidence of measurement error in the income data from NIDS (Lechtenfeld and Zoch, 2014). Since we use income, consumption and saving as outcome variables, measurement errors in outcome variables should still yield unbiased coefficients.

We inflation-adjust income and consumption to take into account 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 (Statistics South Africa, 2010, 2012, 2014). We log-normalize income, expenditure and saving. Data from three households were identified as outliers and removed from the dataset.

We construct two saving measures. The first measure (SAV1) is simply income minus expenditure. This measure is likely to underestimate saving because expenditure includes durable expenditure, which inherently includes some elements of saving since the value of such expenditure should be depreciated over time. In the second measure, we exclude durable expenditure, which comprises items such as household maintenance, furniture, and clothing. Hence our saving measure is income, minus expenditure, plus durable expenditure.

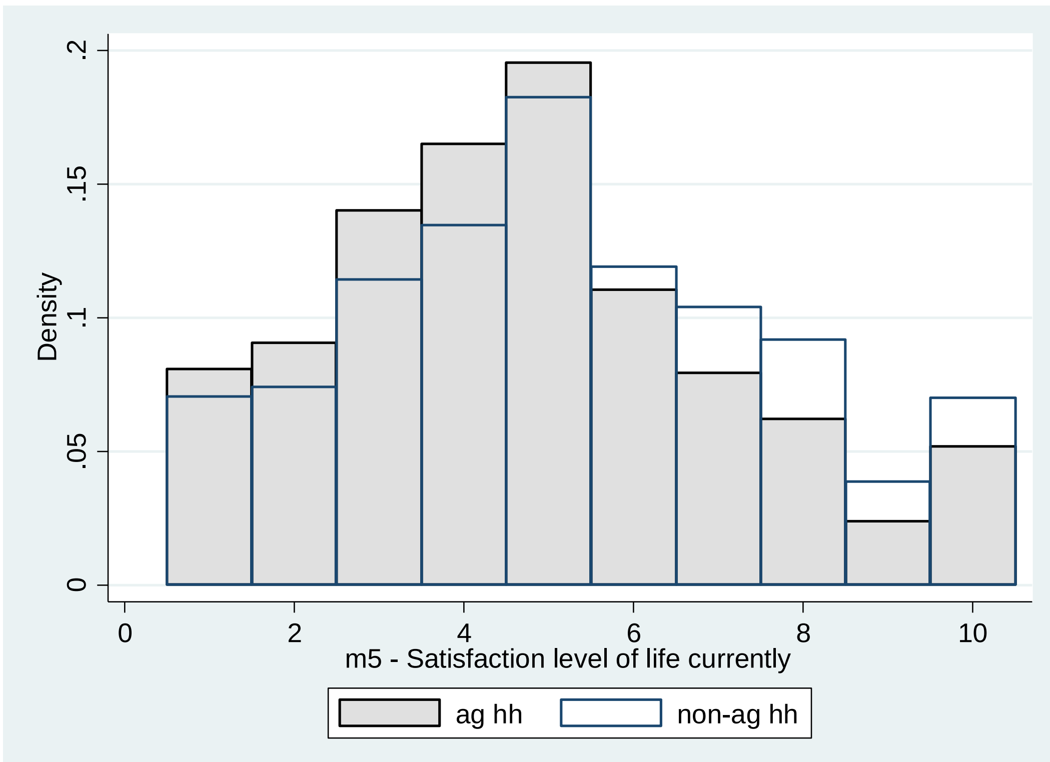
3.2.2. Temperature and precipitation data

We construct two sets of rainfall variables and three sets of temperature variables, matching these data to each of South Africa's 52 districts, using GPS coordinates.[8] We created a 26-by-23 units grid covering South Africa, with each grid representing a 0.75-by-0.75 degree GPS area. Within each of the 26-by-23 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 climate data. See Appendix D for descriptive summary of weather data.

We construct weather variables from district-matched climate data, according to planting, growing and non-agriculture seasons in South Africa (VAM, 2015). 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. Furthermore, we construct the coefficient of variation by season to account for variation in the standard deviation. 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).

3.2.3. Well-being and HIV testing

To evaluate the effect of saving behavior on well-being, we leverage survey data on health and well-being. The NIDS include specific questions on life satisfaction. For each wave, the respondent is asked "Using a scale from 1 to 10, where 1 means 'very dissatisfied' and 10 means 'very satisfied', how do you feel about your life as a whole right now?" We take the response of head of household to assess any changes in life satisfaction of the household. Figure 1 outlines the distribution of responses to this question across agriculture and non-agriculture households for the pooled dataset. The self-reported life satisfaction level for non-agriculture households is 5.23 and for agriculture household is 4.77 (with standard deviations of 2.46 and 2.33 respectively). There is a statistically significant difference of satisfaction level for non-agriculture households compared to agriculture households ($p<0.001$), which indicates that household heads of non-agriculture households express a greater satisfaction with life than agriculture household heads.



Note: Life satisfaction is measured by the question: "Using a scale of 1 to 10 where 1 means 'very dissatisfied' and 10 means 'very satisfied', how do you feel about your life as a whole right now?"

Figure 1: Distribution of life satisfaction among households

We further examine the effect of saving behavior on health behavior, which we approximate using information on HIV testing. South Africa has a heavy HIV/AIDS burden with the disease accounting for 33.2% of the causes of death in 2012 (WHO, 2012). Starting in 2010, the NIDS captures a question on whether an individual has taken an HIV test. The response rate of this question is 76% to 83% (either yes or no) by year.[9] There is a substantial increase in the prevalence of HIV testing from 2010 to 2012, presumably because of the effect of the government program to expand HIV testing across the country, which was launched in 2010 (Maughan-Brown, Lloyd, Bor, and Venkataramani, 2016). Table 3 outlines the summary statistics for the HIV testing variable.

Table 3: HIV testing by households by year

% with response "Yes"	2010	2012	2014
Non-agriculture	61	81	83
Agriculture	58	82	85
Individual response rate	*76*	*83*	*82*

Note: HIV testing represents individual answers to the question of "I do not want to know the result, but have you ever had an HIV test?"

In the next section, we outline our empirical approach based on the combined weather and household data.

3.3. Empirical approach

3.3.1. Joint significance of permanent and transitory income on saving

First, we construct measures of permanent and transitory income, and we evaluate the propensities to save. To do this, we follow Paxson (1992). Given an additively separable utility function, we derive a saving equation that is linear in permanent income, transitory income, and income variance. This saving equation is a slight variation[10] from Equation 8 in Section 2 as we allow for isoelastic utility by adding a time component to income variance variable *VAR*. It takes the following form:

$$S_{irt} = \alpha_o + \alpha_1 Y_{irt}^P + \alpha_2 Y_{irt}^T + \alpha_3 VAR_{irt} + \alpha_4 W_{irt} + \varepsilon_{irt} \tag{9}$$

Where S_{irt} is saving for individual *i*, in district *r*, at time *t*. Y_{irt}^P represents the permanent portion of the individual's income, while Y_{irt}^T is the transitory portion. VAR_{irt} represents income variation of individual *i* in district *r*, at time *t*, and W_{irt} is a set of household lifecycle characteristics. As presented in Section 2, the standard model would predict that $\alpha_1$should be close to zero, while α_2 should be close to one. The estimated α_3 is a measure of risk aversion and should be greater than zero.

We estimate permanent income as:

$$Y_{irt}^P = \beta_{ir}^P + \beta_1 X_{irt}^P + u_{irt}^P \tag{10}$$

where X_{irt}^P includes a set of variables that capture the household's assets and demographic characteristics. Following Paxson (1992), 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 quintiles in order to reduce potential measurement error in the explanatory variables. Furthermore, we construct household lifecycle structure by categorizing household members by age, gender and education levels. The lifecycle structure of the households is divided into 13 categories, as described in Appendix E. β_{ir}^P captures household fixed effects, and u_{irt}^P is the 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.

$$Y_{irt}^{T} = \beta_t^{T} + \beta_2 X_{irt}^{T} + u_{irt}^{T} \tag{11}$$

where X_{irt}^{T} represent a set of parameters that characterize district-level 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_{irt}^{T} is the error term.

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

$$Y_{irt} = \beta_t^{T} + \beta_{ir}^{P} + \beta_1 X_{irt}^{P} + \beta_2 X_{irt}^{T} + u_{irt} \tag{12}$$

The saving equation can therefore be expressed as:

$$\begin{aligned} S_{irt} = \alpha_o + \alpha_1(\beta_{ir}^{P} + \beta_1 X_{irt}^{P} + u_{irt}^{P}) \\ +\alpha_2(\beta_t^{T} + \beta_2 X_{irt}^{T} + u_{irt}^{T}) \\ +\alpha_3 VAR_{irt} + \alpha_4 W_{irt} + \varepsilon_{irt} \end{aligned} \tag{13}$$

After simplification, the saving equation can be written as:

$$S_{irt} = \gamma_t + \gamma_{ir} + \gamma_1 X_{irt}^{P} + \gamma_2 X_{irt}^{T} + \gamma_3 VAR_{irt} + v_{irt} \tag{14}$$

Where γ_t is time fixed effects $\alpha_2\beta_t^{T}$, $\gamma_{ir}$is the constant α_o and household fixed effects $\alpha_1\beta_{ir}^{P}$, $\gamma_1$is $\alpha_1\beta_1$, $\gamma_2$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.[11]

We first undertake the regression of saving equation as specified in Equation 14. We want to 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. The coefficient γ_3 represents the significance of risk measure in the saving equation. The results of the test of joint significance of income are presented in Section 4.1 and 4.2 for the overall sample, and for agriculture households vs. non-agriculture households.

3.3.2. Estimation of propensity to save and measure of risk aversion

Next, we undertake a procedure to estimate the propensities to save and consume 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 12. We use the estimated coefficients to construct permanent income $\widehat{Y_{irt}^{P}}$, and transitory income $\widehat{Y_{irt}^{T}}$. In the second step, we estimate the saving equation using the fitted values.

$$S_{irt} = \alpha_1 \widehat{Y_{irt}^{P}} + \alpha_2 \widehat{Y_{irt}^{T}} + \alpha_3 VAR_{irt} + \alpha_4 W_{irt} + \alpha_5 \widehat{u_{irt}} + w_{ir} + v_t + \varepsilon_{irt} \tag{15}$$

We include the residual from the income regression, $\widehat{u_{irt}}$, 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 E.

We also estimate the effect of constructed permanent and transitory income on consumption with the following specification.

$$C_{irt} = \alpha_1 \widehat{Y_{irt}^{P}} + \alpha_2 \widehat{Y_{irt}^{T}} + \alpha_3 VAR_{irt} + \alpha_4 W_{irt} + \alpha_5 \widehat{u_{irt}} + w_{ir} + v_t + \varepsilon_{irt} \tag{16}$$

We include two consumption variables, which corresponds to the two saving variables. The difference is in the inclusion of durable consumption.

3.3.3. Tests for extensions of the standard consumption model

We test extensions of the standard consumption model with the following approach.

Precautionary Saving: 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. Since we assume that the underlying utility function is isoelastic, we expect that this coefficient is significantly different from zero (Berg, 2013; Jappelli and Pistaferri, 2010).

Myopic consumption: Following Berg (2013) and Jappelli and Pistaferri (2010), we look at consumption responses to positive and negative income changes. We specify a regression using interaction terms for *ex-ante* income increase. The variable *INC* is an indicator variable that takes the value of one if there is an *ex-ante* income increase. If there is an *ex-ante* income increase, then the coefficient for $\widehat{Y_{irt}^{P}}$ becomes $\alpha_1 + \alpha_7$, the coefficient for $\widehat{Y_{irt}^{T}}$ becomes $\alpha_2 + \alpha_8$, and the coefficient for $\widehat{u_{irt}}$ becomes $\alpha_5 + \alpha_9$.

$$C_{irt} = \alpha_1 \widehat{Y_{irt}^{P}} + \alpha_2 \widehat{Y_{irt}^{T}} + \alpha_3 VAR_{irt} + \alpha_4 W_{irt} + \alpha_5 \widehat{u_{irt}}$$

$$+\alpha_6 INC + \alpha_7\left(INC * \widehat{Y_{irt}^{P}}\right) + \alpha_8\left(INC * \widehat{Y_{irt}^{T}}\right) + \alpha_9\left(INC * \widehat{u_{irt}}\right) \tag{17}$$

$$+w_{ir} + v_t + \varepsilon_{irt}$$

In order to test for differences between *ex-ante* income increases and income decreases, we conduct a Chow test on the interaction model, testing the joint significance of all four interaction terms ($\alpha_6, \alpha_7, \alpha_8, \alpha_9$).

3.3.4. Well-being and health behavior

We evaluate the effect of saving on life satisfaction using a conditional ordered logit model. We let W denote life satisfaction of the head of household. We further decompose saving into those contributions from permanent income, and contributions from transitory income. Saving from permanent income (SAV^P) is estimated as $\alpha_1 \widehat{Y_{irt}^P}$ from Equation 15, and saving from transitory income (SAV^T) is estimated as $\alpha_2 \widehat{Y_{irt}^T} + \alpha_5 \widehat{u_{irt}}$. We include the effect of residuals in transitory income as it is often considered as transitory after income regressions on assets and demographics. Household and year fixed effects from Equation 15 are attributed to permanent and transitory components, respectively, following the same rationale as in previous regressions.

$$W_{irt}^* = \alpha_o + \beta_1 SAV^P + \beta_2 SAV^T + u_i + v_t + \varepsilon_{irt} \tag{19}$$

Given that W* is the latent variable that represents the transformation of an ordered multinomial variable with the logistic function, we use the fixed effect ordered logit model as proposed by Baetschmann (2015). This methodology builds upon the Chamberlain method (1980) of conditional logit estimation of a binary variable. In order to fully exploit the information that is available in the multinomial variable, this methodology proposes to expand the database by *n-1* times, and create an ordered set of binary responses on the expanded database. A conditional logit regression on this expanded database can be shown to be consistent and efficient in finite samples (Baetschmann et al., 2015). For HIV testing, since the outcome is a binomial variable, and represents the cumulative incidence of an event, we undertake a hazard ratio analysis that looks at the probability of the event (i.e., HIV test) at each of the three time points in time the information was recorded (2010, 2011, and 2012). We look at two HIV testing groupings, at the household level (where the household is considered to have HIV testing if at least one member has had the test), and at individual level. We cluster the standard error at the household level to account for potential correlations among individuals within a household.[12]

For all regressions we control for household and time fixed effects as described in Section 3, and report testing results with robust standard errors.[13]

4. Results

We report the results of our analysis, proceeding in the order of the empirical approach as outlined in Section 3.3.

4.1. Weather and income on household saving

Table 4 presents the results of the joint significance tests that we use to assess the impact of permanent and transitory variables on income and saving for the whole sample, based on Equation 14.[14] As predicted from previous studies (Paxson, 1992; Hirvonen, 2016), we find significant effect of weather variables on saving, for both measures of saving where durable consumption is considered as either part of saving, or part of consumption. The effect of assets and demographic structure on saving is not significant. This result supports the finding of the standard model, that saving is related to predictors of transitory income, but is not related to predictors of permanent income.

Table 4: Test of joint significance of permanent and transitory factors

Joint significance on saving (F statistic and p-value)	Durable goods as consumption	Durable goods as saving
Permanent ($Ho: \gamma_1 = 0$)	1.02 *(0.432)*	0.89 *(0.546)*
Transitory ($Ho: \gamma_2 = 0$)	3.74***	3.81***

	(0.000)	*(0.000)*

Note: Permanent factors include household asset level and life cycle factors as categorized in Appendix E. Transitory factors include rainfall, temperature and extreme degree-days. Outcome is saving, where durable goods are considered as part of consumption, or as part of saving. F-statistic and p-values are reported. * significant at 5%, ** significant at 1%, *** significant at 0.1%.

We estimated the propensities to save and consume using Equation 15. We find that the coefficient for both permanent income and transitory income are significant for saving, which indicated that the households from this panel save not only in relation to transitory income, but also in relation to permanent income. This result aligns with Paxson's result where she found a propensity to save from transitory income of close to one, but there also exists a smaller propensity to save from permanent income (Paxson, 1992). It is worth noting that the proportion saved out of transitory income is larger than the proportion saved out of permanent income, and this difference is significant for the overall population (p=0.02). For every 1% increase in permanent income, saving increases by 1.06% to 1.19%. For every 1% increase in transitory income, saving increases by 1.83% to 2.34%. For consumption, the coefficient for permanent income is significant, but the coefficient for transitory income is not significant. This aligns with expectations from the standard model, where consumption co-varies with permanent income, but not transitory income.

Table 5: Estimation of propensities to save and consume

Coefficients and standard error	Durable goods as consumption	Durable goods as saving
Propensities to save		
$\hat{y}^P$	1.06***	1.19***
	(0.140)	*(0.228)*
$\hat{y}^T$	1.83***	2.34***
	(0.313)	*(0.462)*

$\hat{\varepsilon}$	1.27***	1.35***
	(0.017)	*(0.036)*
Propensities to consume		
$\hat{y}^P$	0.78***	0.64***
	(0.147)	*(0.176)*
$\hat{y}^T$	0.34	0.44
	(0.290)	*(0.371)*
$\hat{\varepsilon}$	0.40***	0.39***
	(0.018)	*(0.023)*
Ho:(p-values)		
$\hat{y}^P = \hat{y}^T$ in saving	0.019	0.022

Note: Standard errors reported in parentheses. * significant at 5%, ** significant at 1%, *** significant at 0.1%.

We tested for precautionary saving and myopic consumption as presented in Section 3.3.3. Table 6 outlines the test results.

Table 6: Test for standard model extensions

F statistics and p-value	Durable goods as consumption	Durable goods as saving
Precautionary saving ($Ho: \alpha_3 = 0$ *in saving*)	3.43*** *(0.000)*	4.46*** *(0.000)*
Myopic consumption (Chow interaction test)	2.90* *(0.021)*	1.59 *(0.175)*

Note: For precautionary saving, α_3 represent coefficient of income variance variables in the saving equation (Equation 15). For myopic consumption, values shown in table are the F-statistic of the joint significance of the interaction terms. P-values are shown in parentheses. * significant at 5%, ** significant at 1%, *** significant at 0.1%.

The income variance coefficients are jointly significant for the saving equation for both measures of saving. This indicates our underlying assumption of the isoelastic utility function is valid, as there are signs of risk aversion in this population, in line with previous literature (Brick, Visser and Burns (2012). For myopic consumption, we test the null hypothesis that the joint significance of the interaction terms in the consumption regression (Equation 17) is equal to zero. If the null hypothesis cannot be rejected, then there is no difference in consumption between income increases and income declines, and we argue that this represents evidence of myopic consumption. In our findings, we see that the null hypothesis cannot be rejected when durable consumption is considered as saving, thus leaving only non-durable components (e.g., food, utilities) in the consumption measure. Therefore, we conclude that for non-durable consumption, we see some signs of myopic consumption.

4.2. A comparison of Agriculture and non-agriculture households

In Tables 7 and 8, we present the results of regressions and testing in agriculture vs. non-agriculture households. The data represents findings from 28,946 observations of non-agriculture households, and 2,373 observations of agriculture households.

Table 7: Test of joint significance and estimation of coefficients

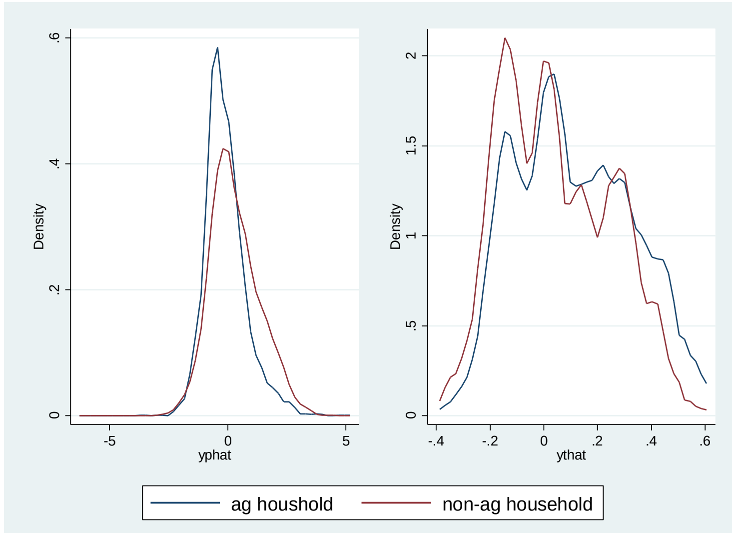
Joint significance on saving (F statistics and p-value)		Durable goods as consumption	Durable goods as saving
Agriculture HH	Permanent ($\gamma_1 = 0$)	1.28 *(0.215)*	1.30 *(0.202)*
	Transitory ($\gamma_2 = 0$)	1.62 *(0.074)*	1.65 *(0.066)*
Non-agriculture HH	Permanent ($\gamma_1 = 0$)	1.32 *(0.186)*	0.94 *(0.515)*
	Transitory ($\gamma_2 = 0$)	2.32** *(0.004)*	2.31** *(0.005)*
Propensities to save (coefficients and standard error)			
Agriculture HH	$\hat{y}^P$	0.52 *(0.319)*	1.25* *(0.517)*

	$\hat{y}^T$	1.38*	2.24*
		(0.627)	*(0.995)*
	$\hat{\varepsilon}$	1.29***	1.32***
		(0.030)	*(0.065)*
Non-agriculture HH	$\hat{y}^P$	1.18***	1.19***
		(0.157)	*(0.254)*
	$\hat{y}^T$	1.85***	2.13***
		(0.370)	*(0.535)*
	$\hat{\varepsilon}$	1.26***	1.36***
		(0.020)	*(0.042)*

Note: Permanent factors include household asset level and life cycle factors as categorized in Appendix E. Transitory factors include rainfall, temperature and extreme degree-days. * significant at 5%, ** significant at 1%, *** significant at 0.1%.

In the saving regression (Equation 14), the result from non-agriculture households align with the overall sample, where weather variables are jointly significant for saving. As expected from the predictions of the standard model, this suggests that the effect of transitory income on saving is significant. For the agriculture households, contrary to what we would expect, we did not find a significant joint relationship between weather variables and saving (p=0.07). Since the livelihood of agriculture households are more likely to be directly linked to weather conditions, we expect this relationship to be more significant for agriculture households than for non-agriculture households. However this finding was not confirmed in our data. This could potentially indicate that we relied on a broad definition of agriculture household. Based on the available data, we include all households where some members engaged in agriculture activities other than earned income over the previous 12 months. Thus we possibly included households where agriculture is supplementary, rather than the main source of income. Therefore, the direct effect of weather on these households may be reduced. The channel with which weather exerts an effect on saving in this panel may be different from the direct effect of weather on agricultural productivity, but more related to other market conditions. These results suggest that it may be important in future research to investigate further the income diversification opportunities of different households groups.

We estimate the propensities to save based on Equation 15 for these two groups. We found similar patterns of propensities to save in non-agriculture households as in the overall sample. The proportion saved out of transitory income is larger than the proportion saved out of permanent income. However, a portion of the permanent income is also saved. In agriculture households, the propensity to save out of transitory income is significant (p=0.03 when durable goods are considered as consumption) but the propensity to save out of permanent income is not significant (p=0.10 when durable goods are considered as consumption). This difference in saving behavior across agriculture and non-agriculture households is potentially due to proportional difference of permanent and transitory income in the subgroups. Figure 2 outlines kernel density distribution of estimated permanent income and transitory income for agriculture and non-agriculture households. Non-agriculture households have more permanent income while agriculture households have more transitory income. Therefore a stronger saving response to transitory income is seen in agriculture households while response to permanent income is not significant as there is simply less.



Note: Graph on the left represent fitted permanent income distribution. Graph on the right represent fitted transitory income distribution.

Figure 2: Kernel density of estimated permanent and transitory income

We also test for precautionary saving and myopic consumption in agriculture and non-agriculture households. Contrary to non-agriculture households, we find no signs of precautionary saving in agriculture households, but the null hypothesis for myopic consumption cannot be rejected. This indicates that agriculture households do not save in response to income variance, after controlling for saving from permanent and transitory income. One explanation for this phenomenon could be that the agriculture households have a simple heuristic for saving, primarily from transitory income, and do not plan for additional saving from the variability of income.

Table 8: Test for model extensions by type of households

F statistics and p-value		Durable goods as consumption	Durable goods as saving
Agriculture	*Precautionary saving*	0.63	1.12

HH	$(Ho\!:\alpha_3 = 0\ in\ saving)$	*(0.817)*	*(0.338)*
	Myopic consumption *(Chow interaction test)*	0.68 *(0.606)*	0.91 *(0.457)*
Non-agriculture HH	*Precautionary saving* $(Ho\!:\alpha_3 = 0\ in\ saving)$	4.06*** *(0.000)*	4.07*** *(0.000)*
	Myopic consumption *(Chow interaction test)*	3.70** *(0.005)*	1.98 *(0.095)*

Note: Data reported represent F statistic of the test for extensions of the standard model. For precautionary saving, α_3 represent coefficient of income variance variables in the saving equation (Equation 15). * significant at 5%, ** significant at 1%, *** significant at 0.1%.

In non-agriculture households, we find evidence of forward-looking behavior in precautionary saving. When durable goods are included in consumption, the myopic consumption test is rejected, meaning that positive income changes lead to different consumption behavior than negative income changes. Possibly, positive income changes lead to purchases of durable goods which has some attributes of saving. This difference disappears when only non-durable consumption is considered. In this case, we find myopic consumption in non-durable consumption such that expenditure for items such as food and utilities are adjusted according to the current period income by the households.

4.3. Effects on life satisfaction and HIV testing investment

Table 9 outlines the result of the regressions on life satisfaction based on Equation 19 and HIV testing for the overall sample, and for agriculture and non-agriculture households. Odds ratios are reported from conditioned ordered logit model grouped at household level. Hazard ratios are reported at both household and individual levels. Standard errors are adjusted by household clusters.[15]

Table 9: Life satisfaction and HIV testing regression on saving behavior

	All	Agriculture	Non-agriculture
Life satisfaction (odds ratio)			
SAV^P	1.27	1.15	1.29
SAV^T	1.14***	1.14**	1.14***
HIV testing (household hazard ratio)			
SAV^P	1.05***	1.05***	1.05***
SAV^T	1.00	1.00	1.00
HIV testing (individuals hazard ratio)			
SAV^P	1.06***	1.06***	1.06***
SAV^T	0.97	0.99	0.97

Note: Regression using saving where durable consumption is not included, and is estimated from income based on assets and households lifecycle factors, including fixed effects. Household fixed effects are attributed to saving from permanent factors, year fixed effects are attributed to saving from transitory factors. Odds ratio is presented for life satisfaction and hazard ratios are presented for HIV testing at the household and individual levels. * significant at 5%, ** significant at 1%, *** significant at 0.1%.

Increased log-saving from transitory income increases the odds of a one-unit increase in life satisfaction by 14%. Increased saving from permanent income did not have a statistically significant effect on life satisfaction. In terms of HIV testing, the results at the household level and individual level are consistent. One step increase in log-saving from permanent income leads to a 5% to 6% increase in incidence hazard ratio of HIV testing. This is also consistent across non-agriculture and agriculture households. This potentially indicates that saving from transitory income, although saved, is not seen as earmarked for spending such as HIV testing, which could be seen as a “preventative” healthcare measure. This interpretation is in congruence with findings from Dupas and Robinson (2013), where they found that even saving earmarked for health were more likely to be used in emergency settings rather than preventative settings. Since HIV testing is a preventative measure, saving from a transitory income change may not be associated with such behavior and is reserved for more urgent threats such as emergencies. Furthermore, it could indicate that health preventative behavior may require a stronger inducement than a temporary injection of income or saving, in that only a change in fundamental factors such as assets or demographic advantages leads to a significant difference in such behavior.

5. Conclusion

We evaluate consumption and saving behavior of South African households from 2008 to 2014, using a newly available, comprehensive household panel, which we enrich with daily weather data for a time period of over 30 years. The novelty of our analysis lies in the additional evidence on household consumption and saving behavior in a developing country, and the comparative differences between agriculture households and non-agriculture households within the country. Furthermore, we evaluate the effects on a welfare indicator, life satisfaction, and health behavior in the case of HIV testing. The latter test is particularly relevant for South Africa, which has one of the highest HIV disease burdens around the world.

Our results mostly confirm findings in other relevant literature. Using fixed effect models with both household and year fixed effects, we evaluate within household variation in saving behavior in relation to income changes. We find that in this time period, South African households save in relation to both their transitory income and permanent income, although the proportion saved from transitory income is significantly higher than permanent income. This aligns with findings from previous studies in developing countries (e.g., Thai rice farmers by Paxson (1992)). We also find evidence of precautionary saving and myopic consumption on non-durable consumption in our sample households. This indicates that households adjust for the consumption of non-durable items such as food and utility in order to cope with income changes.

Compared to non-agriculture households, agriculture households do not exhibit evidence of precautionary saving, but show evidence of myopic consumption regardless of the accounting of durable goods. Agriculture households tend to have less income from permanent factors (e.g., assets, demographic advantages), and more income from transitory factors (e.g., favorable weather). While these households tend to save from transitory income, we do not find evidence that they save in addition to changes in transitory income.

When we evaluate the relationship between life satisfaction on saving as it relates to permanent and transitory income, we find that there is a 14% increase in odds of a step increase in life satisfaction when saving from transitory income is increased. This enhancement in life satisfaction exists for both agriculture and non-agriculture households. Furthermore, saving from permanent income is associated with a 5% increase in the incidence (hazard) of undertaking an HIV test at the household level, and a 6% increase in the incidence (hazard) at the individual level. This indicates factors that drive saving from permanent income (i.e., assets and demographic advantages) could lead to a significant advantage in individual or household healthcare behavior, such as seeking or complying with an HIV test. For households which are disadvantaged in such factors (e.g., agriculture households), a shift in these fundamental aspects will lead to more health seeking behavior. Alternatively, a temporary injection of income has no effect on HIV testing, thus suggesting that programs aimed at encouraging preventative health behavior need to focus on improving fundamental factors.

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Endnotes

1. Myopic consumption stipulates that an individual consumes in relation to income only in the current period. This model assumes no consumption smoothing, and its predictions are in contrast to the perfect foresight assumed in the rational consumption model (Berg, 2013). Precautionary saving is a risk management behavior where the individual saves in relation to income variance in addition to income levels.
2. The terms “subjective well-being” and “life satisfaction” are used interchangeably in this paper. An example of recent studies that examine the relationship between income and life satisfaction is Gokdemir and Dumludag (2012).
3. The indicator of “self-reported life satisfaction” in the South African context, specifically using various waves of NIDS dataset, has been used in other research as an indicator of life satisfaction (Botha, 2014). Such self-reported response has also been used in other studies on life satisfaction. Howell (2006) used a 5-item Satisfaction With Life Scale (SWLS) survey for the measure of life satisfaction in Malaysia. Obucina (2013) and Gokdemir (2015) used a single question on life satisfaction with a scale of 0 to 10 from the German Socio-Economic Panel (GSOEP) and from the Turkish Life in Transition Survey (LiTS), respectively.
4. Climate normals refer to a location’s weather averaged over a long period of time (e.g., 30 years).
5. Isoelastic utility function (i.e., power utility function) exhibits constant relative risk aversion (CRRA). It is of the form $u(c) = \begin{cases} \frac{c^{1-\gamma}-1}{1-\gamma}, & \gamma \neq 1 \\ \ln(c), & \gamma = 1 \end{cases}$, where $\gamma > 0$ is a constant and a measure of relative risk aversion. There is recent evidence of risk aversion from

South African fishing communities based on an experimental study (Brick, Visser, and Burns, 2012).

6. The 52 districts can be further divided into two types: district municipalities and metropolitan municipalities. The 8 largest urban districts are metropolitan municipalities which incorporates both district and local municipalities. The 44 others are district municipalities which are further divided into 226 local municipalities within the districts (Statistics South Africa, 2011).
7. For 2008, we have directly reported income data from 5,424 (out of 7,273) households. In addition, we have income categories (from showcards) from 472 households. This represent a “missingness” of 19%. Income data from US National Health Interview Survey had a missing data range of 24-34% for the “exact” value and 20-31% for the category value (Schenker et al., 2010). The “missingness” in our dataset in 2010 was 25%, in 2012 was 20%, and in 2014 was 18%.
8. We identify the GPS coordinates corresponding to each district with GPS application Latitude.to which combines geolocation information from other internet sources (Latitude.to, 2016).
9. The survey does not capture the true disease prevalence of HIV/AIDS in the sample population. For the disease of HIV/AIDS, it relies on individual’s self-reporting in the categories of “other illnesses”, and it does not allow interviewer to give a reminder about a particular disease. Using this methodology, the reported prevalence of HIV/AIDS in the population is less than 3%. The survey, however, asks a separate question on HIV testing. In asking this question, the interviewer stresses that (s)he is not interested in the result of the test, but just want to know whether a test was taken.

10. Our data allows us to evaluate time variant income variance, therefore, we included this variable in our version of the saving equation. In Paxson (1992)'s original specification, income variance is time-invariant, and since it is represented by standard deviation of rainfall, is also invariant across households within a region. In our specification, income variance is household invariant within a district, but is time variant. We proxy income variance by coefficient of variation of rainfall and temperature, which is standard deviation divided by mean for every season from 2008 to 2014.
11. We include income variance in the saving regression when testing for joint significance. We assume the utility function can be constant relative risk aversion (CRRA) utility, which allows us to use log-normally distributing saving as the outcome variable. This also implies that the coefficient for the income variance is significant. Not including income variance can potentially lead to omitted variable bias.
12. We are potentially concerned about omitted variables in the HIV regression, which could lead to endogeneity problems. For example, the availability of clinics or the roll-out schedule of the government program could have an impact on HIV testing status of the household, and be related to household demographics or asset level. We are able to account for some of these unobserved characteristics in the household and year fixed effects. However it is possible that there exists variables that are both household-variant and time-variant that are absorbed in the error term which could lead to a potential correlation between the error term and the explanatory variables. This has not been accounted for in the current regression.
13. The regression results of income and saving from permanent and transitory factors (Equations 12 and 14) are in Appendices F, G and H. Each appendix presents the results

for the whole sample, as well as for separate estimations for agriculture and non-agriculture households. The coefficients for individual elements of the regression are mostly non-significant. However, we are interested in the joint significance of the factors and the test results are presented in Table 4.

14. For all household and year fixed effect regressions, we test robustness by incorporating potential spatial correlation as noted by Conley (1999). We do this with code reg2hdfespatial by Thiemo Fetzer which is the fixed effect modification of code ols_spatial_HAC by Hsiang (2010). We find our transitory income elements to be robust with the spatial correlation. With a 25km cut off distance, our current interpretation is unchanged.
15. We also tested the impact on self-reported children's health status and did not find any significant contribution from saving as specified in the life satisfaction regression. We also conduct a cross-sectional test on fertility as represented by incidence of pregnancy and that did not yield any significant result.

Appendix

a. Household data description

In the first stage, 400 primary sampling units (PSUs) were selected from Stats SA's 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 worker's hostels, convents and monasteries. Gauteng and KwaZulu-Natal are the two largest provinces with population of 20 million while Northern Cape is the smallest province with population of over 2 million (Statistics South Africa, 2011). 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, 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

b. Household descriptive data

Household statistics	Non-agriculture	Agriculture
% of HH with Facilities		
Owned dwelling***	74	94
Piped water***	69	38
Electricity for cooking***	71	42
Mobile phone***	83	86
Demographic characteristics		
Avg # of adults (15+) in household***	3.0	3.9
Avg # of children in household***	3.0	3.8
Avg age of household head***	49	56
% female as household head***	47	57
Avg # of births per female***	2.4	3.0
% of African or colored race***	91	97
% heads with education of Grade 12***	22	7
Fees spent on education in 2007 for adults (rand)***	1142	429
Fees spent on education in 2007 for children (rand)*	441	219

% heads reporting good health***	72	54
Avg birth weight of children (kg)**	3.1	3.2
Avg head circumference of children at birth (cm)***	34.3	34.7

Note: * significant at 5%, ** significant at 1%, *** significant at 0.1%.

c. Household income, expenditure and saving

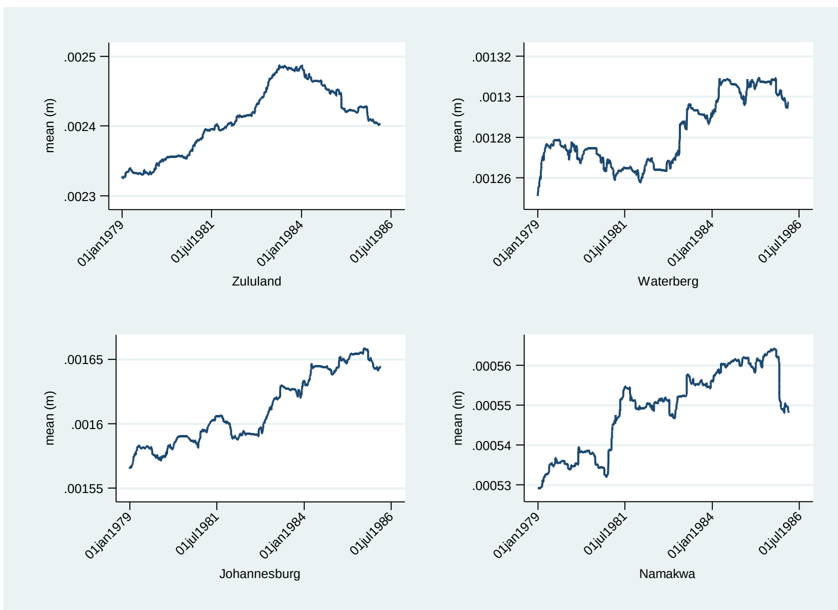
	Rand	Income	All expenses	Durable expenses	Saving (v1)	Saving (v2)
2008	Non-agriculture	3672	2253	462	1586	2105
		(8045)	*(4932)*	*(2378)*	*(6157)*	*(6928)*
	Agriculture	2290	1671	253	715	944
		(9214)	*(9397)*	*(1941)*	*(13143)*	*(13919)*
2010	Non-agriculture	4185	1973	430	2300	2929
		(15710)	*(14732)*	*(5303)*	*(21371)*	*(22776)*
	Agriculture	2420	1095	342	1353	1761
		(6235)	*(2368)*	*(2555)*	*(5760)*	*(6250)*
2012	Non-agriculture	4423	2436	239	2013	2337
		(12311)	*(8054)*	*(1256)*	*(13644)*	*(13794)*
	Agriculture	2816	1849	298	992	1326
		(5422)	*(13578)*	*(2576)*	*(12340)*	*(12678)*
2014	Non-agriculture	4651	2725	365	1938	2430
		(7273)	*(4777)*	*(3157)*	*(5936)*	*(7140)*
	Agriculture	3653	1855	205	1815	2031
		(11894)	*(3398)*	*(1336)*	*(11347)*	*(11469)*

Overall	Non-agriculture	4195	2340	377	1947	2437
		(11287)	*(8884)*	*(3379)*	*(13207)*	*(14027)*
	Agriculture	2793	1622	275	1229	1527
		(8560)	*(8596)*	*(2174)*	*(11035)*	*(11447)*

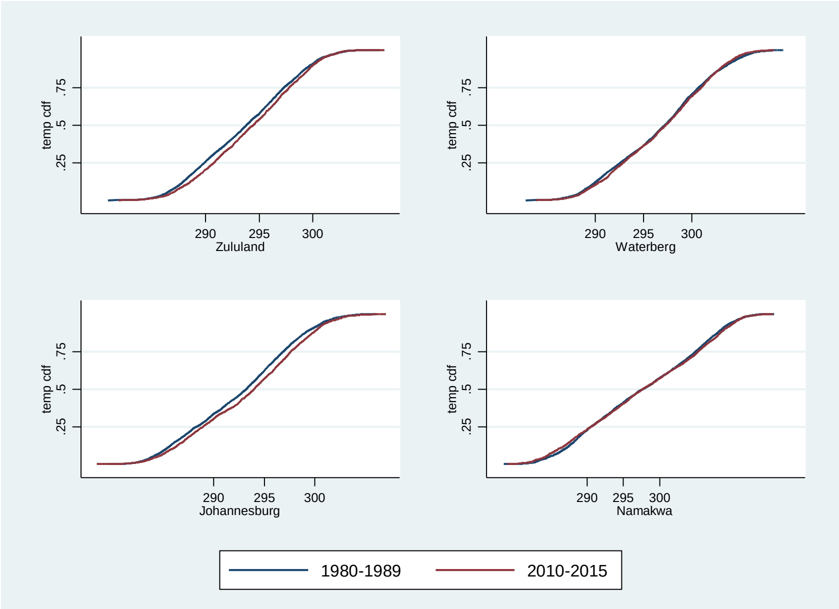
Note: standard deviation in parenthesis.

d. Descriptive data on weather variables

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



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



Source: ERA-interim dataset and author's elaboration

e. Household structure

Category	Age	Gender	Education
1	< 5		
2	6 to 11	Male	
3	6 to 11	Female	
4	12 to 17	Male	
5	12 to 17	Female	
6	18 to 64	Male	< 7 years
7	18 to 64	Male	7 to 9 years
8	18 to 64	Male	> 9 years
9	18 to 64	Female	< 7 years
10	18 to 64	Female	7 to 9 years
11	18 to 64	Female	> 9 years
12	> 65	Male	
13	> 65	Female	

f. Income regression (Equation 12)

Outcome	All	Agriculture	Non-agriculture
Assets	0.06***	0.06***	.06***
Demographics (Appendix D)			
Category 1	0.00	0.01	-0.00
Category 2	-0.00	0.05	-0.02
Category 3	0.02	0.01	0.03
Category 4	-0.00	0.04	-0.01
Category 5	0.01	-0.06	0.04
Category 6	0.01	0.02	0.01
Category 7	0.03	0.15*	-0.01
Category 8	0.06*	0.13*	0.05
Category 9	-0.02	-0.01	-0.03
Category 10	0.04	-0.02	0.05
Category 11	0.01	-0.06	0.04
Category 12	0.06	0.21*	0.02
Category 13	-0.04	-0.01	-0.05
Rainfall, deviation from norm			
Planting season	0.85**	0.76	0.81*
-- Square term	-2.44	4.84	-3.49
Growing season	-0.36	1.05	-0.74*
-- Square term	2.99	-4.91	8.12**
Other season	0.22	-1.01	0.52
-- Square term	3.51	-3.15	4.15
Temperature, deviation from norm			
Planting season	0.04*	0.02	0.03
-- Square term	-0.00	-0.02	-0.00

Growing season	0.00	0.03	0.01
-- Square term	-0.00	-0.00	-0.01
Other season	0.03	-0.02	0.04
-- Square term	-0.02	0.01	-0.03*
Extreme hot days	-0.00	0.00	-0.01*
Model constant	7.47***	7.01***	7.64***
Model F stat	24.87***	8.73***	18.56***

legend: * p<.05; ** p<.01; *** p<.001

g. Saving equation with durable goods as consumption (Equation 14)

Outcome	All	Agriculture	Non-agriculture
Assets	0.03**	0.01	0.04**
Demographics (Appendix D)			
Category 1	0.07	0.20	0.02
Category 2	0.05	0.30*	-0.03
Category 3	0.10	0.15	0.09
Category 4	-0.01	0.12	-0.06
Category 5	0.06	-0.04	0.10
Category 6	0.05	0.24	-0.02
Category 7	0.05	0.22*	-0.01
Category 8	0.01	0.12	-0.01
Category 9	-0.01	-0.10	0.06
Category 10	-0.01	0.05	-0.03
Category 11	0.01	-0.08	0.04
Category 12	0.04	0.20	0.01
Category 13	-0.07	0.11	-0.14
Rainfall, deviation from norm			
Planting season	0.67	0.64	0.66
-- Square term	1.25	16.53	-2.30
Growing season	-0.54	-0.26	-0.70

-- Square term	-6.20	-16.17	-1.26
Other season	1.10	0.89	1.06
-- Square term	19.16**	23.75	16.37*
Temperature, deviation from norm			
Planting season	-0.00	0.03	-0.01
-- Square term	-0.01	-0.05	-0.01
Growing season	-0.16**	-0.22	-0.13*
-- Square term	0.00	0.03	-0.00
Other season	0.22***	0.16	0.24***
-- Square term	-0.09***	-0.09	-0.09**
Extreme hot days	0.00	0.01	0.00
Rainfall, coefficient of variation			
Planting season	-0.08	0.14	-0.07
-- Square term	0.43*	0.29	0.48*
Growing season	0.11	0.01	0.14
-- Square term	0.02	-0.02	0.02
Other season	-0.08*	-0.07	-0.09*
-- Square term	-0.01	-0.00	-0.01
Temperature, coefficient of variation			
Planting season	-16.98	2.89	-22.18
-- Square term	2.69	-4.19	3.99
Growing season	-6.46	-3.89	-6.10
-- Square term	54.45	-9.05	72.52
Other season	-0.13	25.42	-6.18
-- Square term	16.12	8.31	16.12
Model constant	7.19***	5.41	7.48***
Model F stat	4.04***	2.01***	3.22***

legend: * p<.05; ** p<.01; *** p<.001

h. Saving equation with durable goods as saving (Equation 14)

Outcome	All	Agriculture	Non-agriculture
Asset	0.05**	0.05	0.05*
Demographics (Appendix D)			
Category 1	0.07	0.20	0.03
Category 2	0.10	0.22	0.07
Category 3	0.04	0.07	0.05
Category 4	0.01	-0.02	0.01
Category 5	0.04	-0.04	0.08
Category 6	0.05	0.15	0.02
Category 7	0.01	0.24	-0.11
Category 8	0.03	-0.06	0.06
Category 9	0.01	-0.11	0.08
Category 10	-0.05	-0.27	0.03
Category 11	0.04	-0.13	0.10
Category 12	-0.12	0.11	-0.20
Category 13	0.10	0.32	0.00
Rainfall, deviation from norm			
Planting season	1.61	2.90	1.03
-- Square term	9.42	4.45	10.49
Growing season	0.31	1.19	-0.08
-- Square term	1.70	-8.33	7.41
Other season	1.60	2.00	1.09
-- Square term	22.71**	29.79	13.94
Temperature, deviation from norm			
Planting season	-0.01	-0.05	-0.02
-- Square term	-0.04	-0.02	-0.04
Growing season	0.02	0.01	0.05
-- Square term	0.01	0.03	-0.01
Other season	0.15*	0.07	0.17*

-- Square term	-0.04	-0.07	-0.04
Extreme hot days	-0.00	0.01	-0.01
Rainfall, coefficient of variation			
Planting season	-0.23	0.09	-0.24
-- Square term	-0.05	-0.33	0.09
Growing season	0.24	0.08	0.21
-- Square term	0.04	-0.02	0.04
Other season	-0.01	0.02	-0.03
-- Square term	-0.02	-0.01	-0.01
Temperature, coefficient of variation			
Planting season	-5.68	-20.94	-6.53
-- Square term	2.49	-2.51	6.05
Growing season	-15.43*	-38.82	-11.95
-- Square term	21.60	61.81	25.17
Other season	-0.76	29.47	-13.59
-- Square term	36.67**	66.37*	31.28*
Model constant	7.65***	11.97**	7.22***
Model F stat	5.09***	2.30***	3.87***

legend: * p<.05; ** p<.01; *** p<.001