Income Improves Subjective Well-Being: Evidence from South Africa*

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Abstract

This paper estimates the causal impact of income on life satisfaction for a broad sample of individuals in a developing country. Using a large and representative panel survey of South African residents, we find that receipt of the Older Person's Grant, a means-tested cash transfer that is given to residents age 60 and over regardless of labor force status, increases several household-level measures of economic well-being, resulting in a large and significant increase in subjective well-being. Specifically, the average 20% increase in per capita household income due to this grant increases life satisfaction by approximately 0.2 points—a large effect that extends to all members of the household. The discontinuity in the eligibility of the Older Person's Grant provides a reliable causal estimate of the effect of income on life satisfaction that is larger than OLS estimates.

Keywords: Income, Life Satisfaction, Happiness, Poverty, South Africa, Older Person's Grant.

JEL Codes: I31, I38

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1 Introduction

A large and growing literature investigates the determinants of subjective well-being measures such as happiness and life satisfaction, and in particular, the role that income plays. Studies show, albeit with some significant debate, that income and wealth are positively related to measures of happiness and life satisfaction. This is consistent with most economic models that are based on the assumption that income increases utility, which strongly relates to survey based measures of subjective well-being (Benjamin et al., 2012; Oswald and Wu, 2010). However, several sources of endogeneity make estimating the effect of income on measures of happiness and life satisfaction difficult, and thus, the evidence for the causal impact of changes in income or wealth on subjective well-being is sparse—especially among broadly representative samples in developing countries.

This paper addresses these issues by using the discontinuity in receipt of the Older Person's Grant (a large and unconditional cash transfer) to create a plausibly exogenous instrument for household income and evaluate the effect of increased income on individual life satisfaction using a large panel dataset from South Africa.[1] We contribute to the literature by answering two main questions: First, does household income have a causal impact on an individual's subjective well-being, namely their reported measure of life satisfaction? And second, does accounting for the endogeneity of household income affect the magnitude of the estimated coefficient of income on well-being relative to OLS estimates? The results show that an increase in monthly household income, due to the receipt of a monthly unconditional cash transfer, leads to a large and significant increase in life satisfaction. Using the discontinuity of eligibility for the grant leads to estimates of the income-satisfaction relationship that are nearly twice the size of reduced-form estimates. Specifically, an increase of 20% in monthly household income per capita leads to a 0.2-point increase in life-satisfaction on a 10 point scale. This is larger than analogous esti-

[1] Case and Deaton (1998) analyze the effectiveness of this program on consumption and Duflo (2003) looks at the effect of receipt of the Older Person's Grant in South Africa on intra-household allocation of resources using data from 1993. Our empirical strategy is similar to both studies, whereby we restrict our sample to households with members around the eligibility age of 60. However, with a significantly larger dataset, we are able to use tighter age ranges around the cutoff and restrict our analysis to those who are out of the labor force, giving more credence to the causal estimates. In addition, eligibility criteria for the grant are no longer different for men and women as they were in 1993.

mates found in prior studies that analyze a causal impact of income on life satisfaction, such as Frijters, Haisken-DeNew and Shields (2004) (about 0.1 on a 10-point scale) and Powdthavee (2010) (approximately 0.05 on a 7-point scale). Importantly, we find that this effect extends to all members of the household, not just the grant recipients.

This analysis adds to an inconclusive literature on the impact of income on subjective well-being. In a seminal paper, Easterlin (1974) compares income and happiness across countries and finds that individuals in richer countries, on average, did not appear to be happier than those living in poorer countries. This finding seemed to defy expectation and is dubbed the Easterlin paradox. However, in the same study and in several studies since, Easterlin shows that within countries, the poor exhibit consistently lower levels of happiness than the rich (Easterlin, 1974, 1995, 2001). Moreover, recent careful analyses that use data from many countries around the world show that subjective well-being and income are positively correlated both within and across countries (Graham, 2011; Di Tella and MacCulloch, 2008; Sacks, Stevenson and Wolfers, 2010; Wolfers, Sacks and Stevenson, 2012; Stevenson and Wolfers, 2013).

Fewer studies estimate the causal impact of income on subjective well-being. Exceptions include Frijters, Haisken-DeNew and Shields (2004), who use an increase in income due to German reunification to estimate the effect of income on life satisfaction, and Gardner and Oswald (2007) who find that individuals who win medium sized lottery prizes have significantly better levels of psychological well-being than those who win small prizes or those who do not win at all. Powdthavee (2010) uses the existence of payslips as an instrument for household income and finds large effects on individual happiness, arguing that correlational methods likely understate the effect of income on subjective well-being. Moreover, Haushofer and Shapiro (2016) show that unconditional cash transfers increase life satisfaction and psychological well-being among a sample of very poor rural individuals in Kenya. However, recent work has suggested that the long-term effects of lottery windfalls on mental health and happiness are significantly smaller than the effects on life satisfaction (Lindqvist, Östling and Cesarini, 2020).

The study most closely resembling ours is the recent work by Cuong (2020), which shows that the receipt of a social pension in Vietnam at the age of 80 increases life satisfac-

tion for a sample of elderly recipients. While our analysis similarly uses the discontinuity of receipt of a transfer to older individuals in a developing country, it is distinct in several ways. The South African Older Person's Grant is a large unconditional cash transfer amounting to approximately 140% of the per capita poverty line that begins at the much lower age of 60. In addition, we track the effects of the grant on the subjective well-being of other household members who, given that multi-generational households are common in South Africa, span all adult age groups but are, on average, poorer and slightly younger than the overall representative sample.

Our empirical approach relies on two important conditions. First, having a household member be eligible for the grant must appreciably increase household income, and second, the eligibility for the grant must only improve subjective well-being through its impact on the household's economic well-being as proxied by income per capita. We show that the eligibility for the grant clearly increases household income per capita, and we restrict our sample to only include members of households with economically inactive individuals narrowly around the threshold to make the second condition more plausible.[2] We show results using continuous fuzzy regression discontinuity designs however, because our running variable is discrete and we have a small number of mass points, our main specification assumes local randomization in narrow windows around the age threshold. While we show balance across eligible and in-eligible households, abrupt changes in unobserved factors for households when their economically inactive member turns 60 pose a threat to our identification.

We show that the grant improves several household-level measures of economic well-being. In addition to estimating the effect of increased income on the life satisfaction of the recipients, we show that this effect extends to other members of the household and is similar in magnitude. We also show that the effect on non-recipients is only statistically significant when the grant recipient is female reiterating, albeit indirectly, conclusions of work that shows heterogeneity in the intra-household distribution of income changes based on the sex of the recipient (Duflo, 2003; Schady and Rosero, 2008; Phipps and Burton, 1998).

[2]While increased economic resources may certainly impact life satisfaction through the mechanism of labor supply changes, we have chosen to abstract from these effects by focusing our analysis on recipients of the grant who are not in the labor force before or after passing the age threshold.

This paper makes an important contribution to the literature by rigorously estimating the causal impact of income on life satisfaction for a broad sample of individuals in a developing country.

The rest of the paper is structured as follows: Section 2 discusses the data and presents motivating descriptive statistics. In Section 3, we outline our main empirical approaches, and show the effect of the grant on household-level measures of economic well-being. We present our main findings with relevant robustness checks in Section 4 and conclude in Section 5.

2 Data and Descriptive Statistics

2.1 Data

The data used in this analysis comes from the panel dataset of the National Income Dynamics Study (NIDS) of South Africa.[3] The first survey wave of this study was conducted in 2008 and households (and individuals) were interviewed again in 2010, 2012, 2014, and 2017. The 2008 sample of nearly 27,000 individuals was nationally representative.[4] Data were collected on many socio-economic variables that include demographic information, income, consumer expenditure, labor market participation, information on self-employment and farming activity, fertility, health, migration, education, and anthropometric measures.[5]

In the individual-level adult survey for those 16 or above, individuals are asked to rate their overall satisfaction with life on a scale of 1 to 10. The specific question in the survey asks: "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?" The data shows a very high response rate—approximately 97% of adults interviewed responded to the life satisfaction question.

The NIDS dataset contains detailed information on household income and expenditure

[3]This is a panel study conducted by the South Africa Labor and Development Research Unit at the University of Cape Town.

[4]15,630 adult individuals in 6,598 households completed questionnaires. Each wave’s sample is refreshed in order to deal with attrition and keep each wave nationally representative.

[5]The data are publicly available: see http://www.nids.uct.ac.za/

in addition to individual income. While we mainly choose to use household income per capita throughout the analysis, we also use food expenditure per capita and a wealth index as measures of economic well-being to test the robustness of some of the key results.[6]

2.2 Descriptive Statistics

South Africa is a middle-income country with the highest level of income and wealth inequality in the world (World Bank, 2018). The mean monthly household income per capita in the study sample in 2017 is ZAR 3,301 with a standard deviation of ZAR 9,666.[7] This hides significant inequality as the median household income per capita is ZAR 1,450. Moreover, in 2017 nearly 50% of the sample is living in poverty and about 20% live in extreme poverty, aligning with recent analysis at the population level (Leibbrandt, Finn and Woolard, 2012).[8]

In our data, the median reported level of life satisfaction on a scale of 1-10 is 5 whereas the mean is slightly higher at 5.27. The standard deviation is 2.45 and this measure of subjective well-being exhibits a relatively low correlation across waves of 0.12 and has a within-person standard deviation of 2.06. A histogram of self-reported life satisfaction for the five waves of NIDS, as seen in Figure 1, is fairly bell-shaped, with the exception of a disproportionate share of individuals marking 10, the highest level of life satisfaction. This phenomenon is consistent with other data in the United States (such as the Behavioral Risk Factor Surveillance System) or in data across many different countries (such as the World Values Survey), where individuals are very likely to report the highest level of life

[6]The household income variable is constructed through the addition of all sources of income to the household including wages, rents, and transfers. We divide by household size to create a per capita income measure. We control for household composition in our analyses and thus our results do not change meaningfully if we use household income per adult equivalent instead of per capita. The wealth index is constructed through factor analysis of household-level dwelling characteristics and durable goods.

[7]This corresponds to 247 US Dollars or $514 PPP adjusted. The distribution of income is extremely skewed (a very large standard deviation). Income and expenditure numbers are adjusted for inflation and are in November 2017 prices.

[8]We use a household income per capita of ZAR 1,138 (official 2017 upper-bound poverty line) to indicate poverty status and ZAR 531 (official food poverty line) to indicate extreme poverty (Lehohla, 2017). In the balanced panel sample of NIDS, 87% of individuals report income per capita levels that are considered poor in at least one of the five waves. However, only 11% are poor in all five waves of the panel. While these poverty dynamics numbers are for individuals in households who are interviewed in all five waves, our analysis is not restricted to the balanced panel.

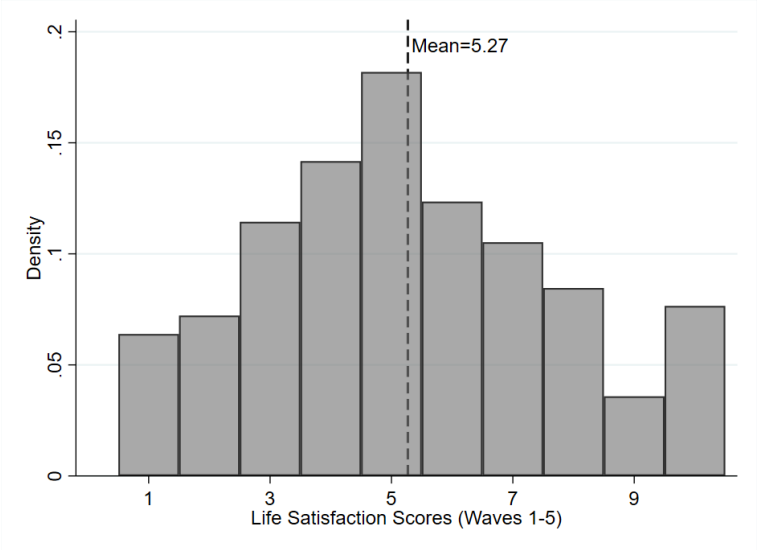


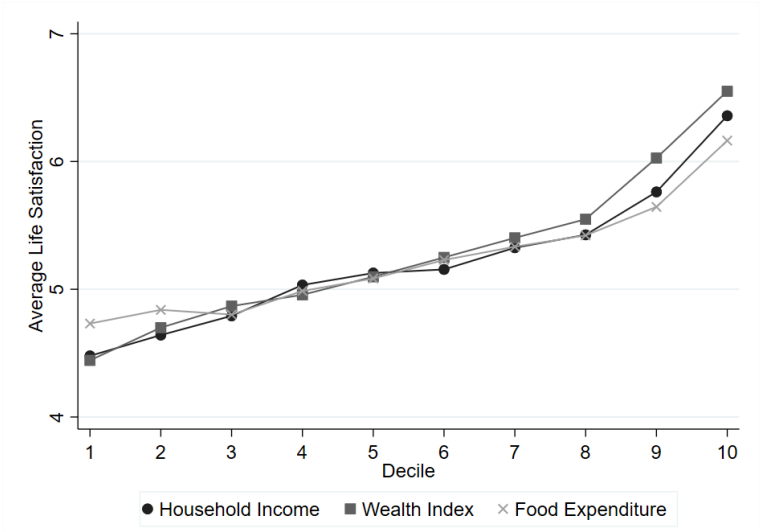
FIGURE 1: Histogram of life satisfaction scores across all five waves. Median and mode life satisfaction scores are 5. A disproportionate share of individuals report the highest level of satisfaction—a phenomenon that is consistent with life satisfaction scores in the United States and many different countries.

satisfaction.[9]

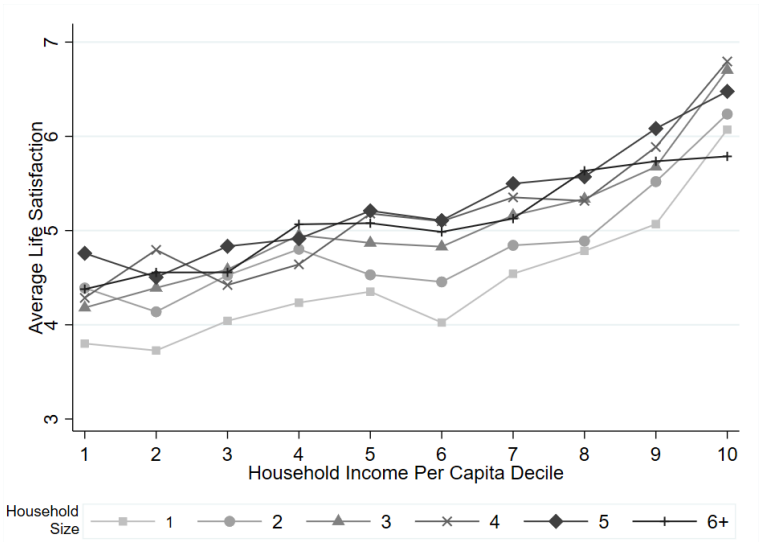
Consistent with other research discussed earlier, Figure 2(A) shows that in our data there are strong positive correlations between life satisfaction and several measures of economic well-being, notably household income, wealth, and food expenditures. The magnitude of these differences is not small: compared to those in the lowest decile, individuals living in households in the top 10% of income per capita report life satisfaction about two points higher on a 1-10 scale, which translates to roughly 0.8 standard deviations. This pattern is not merely masking differences due to the size of the household, as average life satisfaction across household income deciles shows a similar clear positive pattern for different household sizes as shown in Figure 2(B).

While we have shown a correlation between economic and subjective well-being, we have yet to establish any clear directions of causality. The next section outlines our empir-

[9]Table A.1 in the Appendix shows mean life satisfaction scores across different demographic groups and waves. Males report lower levels of subjective well-being than do female respondents and Black respondents also report significantly lower life satisfaction than individuals from other racial groups in South Africa. Being married, living in an urban area, and not being poor are positively related to well-being. There is no clear discernible pattern in the raw unadjusted relationship between age and life satisfaction. Overall life satisfaction increased by about 0.5 points between 2010 and 2017, but the trends vary by race and poverty levels.



(A) Average life satisfaction by different measures of economic well-being



(B) Differentiating by household income per capita and household size

FIGURE 2: Average subjective well-being is increasing with measures that proxy economic well-being. For household income per capita, the bottom figure (B) shows that this pattern is strong even when controlling for household size. Figure A.1 in the Appendix shows a similar, albeit more pronounced, pattern when determining income deciles within each household size group.

ical strategy to estimate the causal effect of economic well-being on subjective well-being.

3 Estimation Approach

We use several approaches to study the relationship between income and subjective well-being. First, we estimate the coefficient on the log of household income per capita using a simple ordinary least squares regressions and fixed effect regressions, and discuss potential sources of endogeneity. We then discuss how we use the receipt of the Older Person's Grant to estimate the causal effect of income on subjective well-being.

3.1 OLS

First, with the entire sample, we use a simple OLS approach to estimate the following equation:

$$swb_{i,d,t} = \beta_0 + \beta_1 h_{i,d,t} + \Theta \boldsymbol{x}_{i,d,t} + \zeta_{t,d} + \delta_i + \epsilon_{i,d,t}$$

where $swb_{i,d,t}$ is the life satisfaction rating (1-10) for individual i living in district d in wave t, $h_{i,d,t}$ is the log of household income per capita, $\boldsymbol{x_{i,d,t}}$ is a vector of time varying individual and household characteristics including household size, number of children in the household, marital status, age (quadratic), sex, race, and education. We also include neighborhood services. $\zeta_{t,d}$ is a district-wave fixed effect controlling for differences in time trends across the 52 districts and δ_i is an individual fixed effect. Finally, $\epsilon_{i,d,t}$ is unobserved error.

Even after controlling for time-varying individual, household, and neighborhood characteristics in addition to district-wave fixed effects in our simple specification, and including individual fixed effects in our fixed effects regression specification, the estimated coefficient cannot be interpreted in a causal manner as there are several other sources of endogeneity, namely omitted variables, measurement error, and reverse causality. There are likely unobserved omitted variables that are correlated with income and simultaneously affect subjective well-being. We use methods proposed by (Oster, 2019) to place lower bounds on our coefficient estimates that account for omitted variable bias. However, other sources of endogeneity include the potential error in the measurement of income and economic well-being, which is common in observational data and can lead to attenuation bias that may be exacerbated in fixed effects regressions (McKenzie, 2012; Bound et al., 1994; Freeman, 1984). Finally, it is difficult to untangle the dual pathways that exist between

economic well-being and subjective measures of well-being. While a change in an individual's income may play a significant role in determining happiness or satisfaction with life, it may be that subjective well-being partly determines an individual's earnings, as happier people may be more productive and/or more likely to be successful in obtaining jobs. In the next section, we discuss how we exploit a discontinuity in the receipt of the Older Person's Grant to overcome the endogeneity of income in this model.

3.2 Discontinuity Due to the Older Person's Grant

To address the endogeneity difficulties discussed in Section 3.1 and estimate the causal effect of income on subjective well-being, we use an exogenous shock to household income through South Africa's Older Person's Grant. This program is South Africa's largest social welfare program that was greatly expanded after the end of Apartheid to target the county's most disadvantaged groups (Van der Berg, 1997; Case and Deaton, 1998). Every South Africa citizen or permanent resident becomes eligible for this old-age transfer program when they turn 60 years old.[10] It is a monthly cash transfer that is means-tested on individual and spousal income and the value of their combined assets, but does not directly depend on one's labor force status.[11] The majority of South Africans fall below this high means test threshold and qualify for the grant. In 2017, nearly ZAR 1,600 a month was given to individuals aged 60 to 74 which is approximately 140% of the poverty line. Almost 80% of individuals are eligible at age 60 and there is high take-up (above 90% of eligible members) of this cash grant (Abel, 2019)—nearly 25% of individuals under 60 live with someone who receives this grant making this an important and far reaching social safety net in South Africa.

In order to use an individual's eligibility for the grant as an instrument for household income per capita, we need to satisfy two assumptions. First, household income must increase due to this eligibility. Second, being an eligible member or having another eligible member in one's household should only affect life satisfaction through its impact on increased economic resources (proxied here by household income per capita). For the

[10] Prior to 2010, males became eligible at 65 while females were eligible at age 60.

[11] In 2017, annual income must be less than ZAR 73,800 for a single person or ZAR 147,600 for a couple, and household assets must be no more than ZAR 1,056,000 for a single person or ZAR 2,112,000 for a couple.

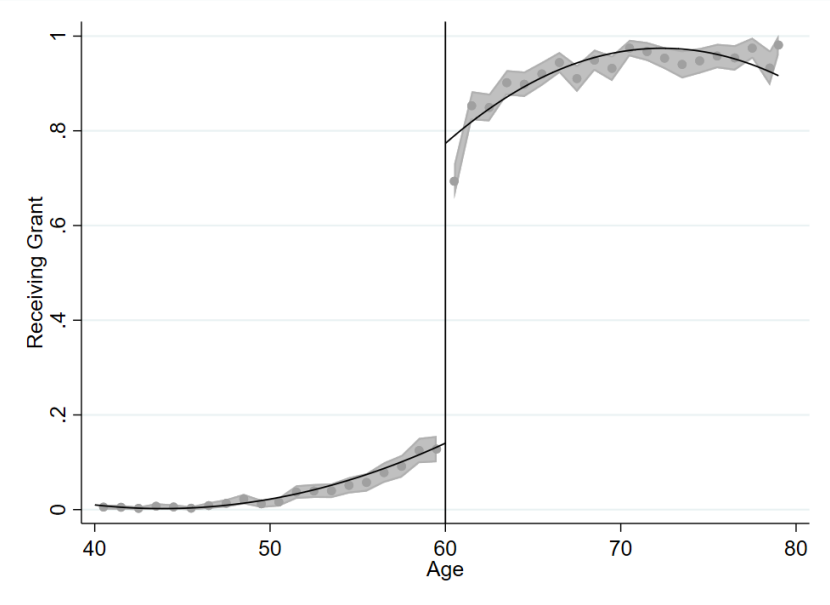


FIGURE 3: Individual-level average receipt of old age grant received by age among all means test eligible. There is a clear jump of grant receipt around the age of eligibility of 60. Figure A.2 in the Appendix shows a similar figure for economically inactive individuals. Figure A.3 shows that this associated with an abrupt increase in household income.

overall sample, this assumption is not plausible: having a 60+ year old as a member of your household can change the household dynamics in a myriad of ways that could also affect life satisfaction. However, the assumption we make in this analysis is that having an *economically inactive* (i.e. not in the labor force) 59 year-old household member is similar to having an *economically inactive* 61 year-old who was also not in the labor force when they were 59—the only difference being that the 61 year-old member is eligible for and likely receiving a grant.

Figure 3 shows, at the individual level, the jump at age 60 in receipt of the Older Person's Grant among those we identify as eligible based on non-pension household income.[12] As soon as individuals turn 60, they become eligible for the program. The application process takes several months, which may explain the slightly lower share receiving at age 60. In addition, due to the means test also being attached to the spouse, it is also more likely at earlier eligible ages that the individual has a working spouse who earns enough to

[12]We use information on the means test to identify individuals in our sample who are very likely above the threshold. We exclude approximately 10% of our sample. Among this excluded group, only 5% above 60 receive the grant whereas among those we keep in our sample 94% receive the grant.

make the individual ineligible. However, the average take-up stabilizes at over 90% after a few years.

While it is clear that grant receipt at the individual level increases at age 60, it is also important for our identification strategy to show that this also increases overall household income per capita. Appendix Figure A.3 shows that the receipt of the grant is associated with an abrupt increase in household income per capita. However, we cannot just compare the incomes of households with members above 60 to those without; households with individuals around the age of 60 differ in important ways from households without such individuals—especially when it comes to economic activity and earnings. Thus in order to investigate whether eligibility for the grant increases household income in a meaningful way, we restrict our sample to households with members who are economically inactive (not in the labor force) and are around the age of 60. We also use the panel nature of the data and further restrict the above-threshold sample to households with individuals who were also not in the labor when they were below the threshold.[13]

This sample restriction makes it more likely that we can satisfy our second assumption: that being 60 or older or having another household member who is age 60 or above only affects life satisfaction through the channel of increased household income. We will show results for various samples that are restricted to five different age ranges (two times the *bandwidth*[14]), all centered around the age of 60. At its widest, we will use a window of six where we restrict the sample to individuals in households with an economically inactive member between the age of 54 and 65 (inclusive).[15] The smallest bandwidth is two, where we only keep individuals who are in households with a member who is economically inactive and is between the age of 58 and 61.

[13]Figure A.4 in the Appendix shows labor force participation around the age of 60—the grant is unconditional and most earn incomes that are well below the means test threshold and thus we do not see a large drop in labor force participation at the age of 60. Nonetheless, we restrict our analysis to households that have a member who does not work and is around the age 60. For households with a member who is above the age of 60, we use information from past waves to determine their labor force participation when they were under age 60 and restrict inclusion in our sample to those who were not in the labor prior to turning 60.

[14]We borrow familiar language from the regression discontinuity literature. This analysis is similar in spirit to fuzzy regression discontinuity designs—however, we have a continuous treatment (household income) and a discrete running variable (age of one of the household members).

[15]This gives us a "bandwidth" or window–as is it referred to in local randomization approaches in the regression discontinuity literature–of 6 around the eligibility cutoff: ages 54, 55, 56, 57, 58, and 59 are in but not eligible for the grant, while 60, 61, 62, 63, 64, and 65 are. Similarly for smaller windows, we successively remove 1 year from each end.

TABLE 1: Balance Table: Age Range 57-62

	Grant-Eligible Group		Non-Eligible Group		p-value
	Mean	SE	Mean	SE	of Δ
Household Level					
Household Size	5.43	0.07	5.37	0.07	0.56
Average Age	35.60	0.28	33.21	0.28	0.00
Number of Children	1.86	0.04	1.82	0.04	0.46
Number of Elderly (66+)	0.25	0.01	0.21	0.01	0.00
Urban	0.43	0.01	0.42	0.01	0.59
Death in the past 2 years	0.11	0.01	0.11	0.01	0.96
Total non-grant income per capita (ZAR)	1,087	309	1,098	264	0.79
Variables expected to change					
Old-Age Grant income per capita (ZAR)	376.4	11.94	108.1	7.93	0.00
Savings	0.36	0.01	0.33	0.01	0.05
Share poor	0.32	0.01	0.38	0.01	0.00
Individual Level (Members around threshold)					
Age	61.02	0.04	58.55	0.03	0.00
Male	0.24	0.02	0.25	0.01	0.62
Married	0.44	0.02	0.43	0.02	0.70
In the Labor force	0.00	0.00	0.00	0.00	
Secondary-Level Education	0.10	0.01	0.10	0.01	0.67
Health Issue in the last 30 days	0.70	0.02	0.73	0.01	0.20
Other Adult Household Members (Excluding members around threshold)					
Age	33.65	0.22	33.07	0.25	0.08
Male	0.48	0.01	0.48	0.01	0.56
Married	0.15	0.01	0.15	0.01	0.86
In the Labor force	0.49	0.01	0.47	0.01	0.17
Secondary-Level Education	0.51	0.01	0.52	0.01	0.70
Health Issue in the last 30 days	0.42	0.01	0.40	0.01	0.17

Notes: This table shows balance for a Age Range 57-62—Balance is similar for all four other age ranges considered below.

Table 1 shows a balance table for this restricted sample that gives credence to the assumption that these households and individuals in them are fairly similar except for eligibility of a member (or members) for receiving a grant.[16] The table shows strong balance at the household-level across these two groups: we cannot statistically differentiate the two groups with respect to household size, number of children in the household, if the household is in an urban area, or if they have experienced a death in the last year. Importantly, average non-grant income per capita does not differ between the two groups. We can however, see differences in household-level variables that we expect to change due to

[16]The table shows the means for the sample restricted to 57-62—the third largest age range: balance is similar for all five ranges considered.

the grant, namely, the average grant income per capita, share who have savings, and share who are poor.

At the individual level, in our restricted sample, the members above and below the threshold are clearly of different average ages. However, we cannot statistically differentiate between the two groups on the share who are male, married, have secondary-level education, or report a health issue in the last 30 days. Because of our sample restriction, all members are out of the labor force. When it comes to other members of the household (not including the recipient or potential recipient), their characteristics are similar across the two groups in terms of the age, sex, marital status, and labor force participation.

After restricting the sample to households with economically inactive members around the age of 60 using several different bandwidths,[17] we show in Table 2 how having a household member eligible for the grant predicts several measures of economic well-being.[18] In our study group, several measures of economic well-being show statistically significant increases at the household level when an economically inactive member around age 60 is eligible for the Older Person's Grant. In our analysis, we use the log of household income per capita as the main measure of income and the economic well-being of the household. The estimates indicate that households with a member eligible for the old-age grant have between 14-20% higher income per capita compared to households with members just below the eligibility threshold. The table also shows that food expenditure increases by about 7% and wealth increases by about 0.1 standard deviations, suggesting that the increase in income at the household level is resulting in measurable changes in expenditure and durable goods for the household. Despite the expectation of the grant, both consumption and durable goods increase on average among households after the individual becomes eligible. This is consistent with credit constraints among the poor in South Africa as shown by Berg (2013).

Now that we have shown that eligibility for the grant increases household income without affecting other characteristics of the households, we now proceed with our estimation

[17] Our sample excludes those above the threshold who are currently out of the labor force but were in the labor force when they were below the threshold.

[18] This can be viewed as a first-stage regression for using grant eligibility as an instrument for household income, though the sample size is smaller because it is at the household-level.

TABLE 2: Improvement in Household-Level Economic Well-being Due to Old Age Grant

	Member Age Range centered at 60				
	54-65	**55-64**	**56-63**	**57-62**	**58-61**
	Household Income Per Capita				
Member Over 60	1.837***	1.727***	1.511***	1.521***	1.294***
	(0.360)	(0.354)	(0.375)	(0.408)	(0.497)
	Log Household Income Per Capita				
Member Over 60	0.197***	0.189***	0.176***	0.166***	0.141***
	(0.022)	(0.022)	(0.023)	(0.025)	(0.030)
	Log Food Expenditure				
Member Over 60	0.077***	0.069***	0.069***	0.064***	0.058***
	(0.015)	(0.015)	(0.016)	(0.017)	(0.020)
	Wealth index				
Member Over 60	0.122***	0.090***	0.103***	0.110***	0.104**
	(0.033)	(0.034)	(0.036)	(0.041)	(0.051)
N	5996	5186	4354	3414	2342

Notes: Standard errors clustered at the original (i.e., wave 1) sampling cluster area are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Household income per capita is in Hundreds of South African Rands. These results are estimated using OLS and restricted to households that have a member around the age of 60 that is a part of our sample that we described in Section 3. We control for wave fixed effects. Results without the means test restriction show similar but slightly weaker results.

of the impact of income on subjective well-being. After restricting our sample to individuals in households with economically inactive members around the age eligibility threshold of 60 (including the recipient and potential recipients of the grant), we use the number of relatives who are at least 60 years or older (but within the respective bandwidth and satisfying our restrictions on labor force participation) as an instrument for household income and estimate the following equation:

$$swb_{i,d,t} = \alpha_0 + \alpha_1 h_{i,d,t} + w_t + \gamma_d + \Gamma \boldsymbol{x}_{i,d,t} + \delta_i + u_{i,d,t}$$

where $swb_{i,d,t}$ is the life satisfaction score (scale of 1-10), $h_{i,d,t}$ is household income per

capita, w_t is a wave fixed effect, γ_d is a district fixed effect,[19] $\boldsymbol{x}_{i,d,t}$ is a vector of time varying individual and household characteristics including household size, number of children in the household, marital status, age (quadratic), gender, race, and education in addition to labor force status, hours worked, and proxies for health. We control for district fixed effects and other neighborhood characteristics as well. Finally we control for the individual fixed effect by running fixed effect instrumental variable regressions. In our results section, we also show the OLS estimates for these restricted samples.

This approach is essentially a fuzzy regression discontinuity design with a continuous treatment (household income per capita); however, our running variable (age of eligible household member) is discrete, resulting in a small number of mass points around the threshold. Thus we use an approach akin to local randomization (Cattaneo, Idrobo and Titiunik, forthcoming) and show results for several different age ranges (windows) around the age of 60 and restrict our sample to individuals who are around the age of 60 as well as those who live in households that have members around this age.[20] To control for confounding factors such as changes in labor force status of the grant recipient, we restrict our sample to households whose member around the age of 60 is economically inactive and use the panel nature of the data to verify that those above the threshold were also economically inactive before.

Potential Identification Issues—There are several issues that could affect the validity of our estimation strategy. We discuss these below and provide some evidence on why we do not think they pose concerns.

Retirement—One of the ways in which our exclusion restriction can be violated is if those above the age of 60 have an increase in life satisfaction that is due to increased leisure time from retirement and not directly through their increased income. Figure A.4 in the Appendix shows no clear discontinuity in labor force participation at the age of 60 that

[19] Unlike in equation (1), due to restriction in sample sizes, we cannot control for district-wave fixed effects as we do in the OLS regressions.

[20] See discussion in Cattaneo, Idrobo and Titiunik (forthcoming): with a small number of mass points around the cutoff, continuity-based regression discontinuity analysis is useful only as an exploratory device without strong parametric assumptions because extrapolation between the mass points becomes unavoidable. In practical terms, the sample size in continuity-based approaches is essentially the number of mass points, which in our case is very small. Cattaneo, Idrobo and Titiunik (forthcoming) suggest local randomization approaches as more appropriate for this type of data.

jumps from the steadily decreasing trend. Nonetheless, we restrict our analysis to individuals around the age of 60 who are out of the labor force beforehand. We use the panel nature of the data to restrict our above 60 sample to individuals who were also out of the labor force before they were 60 years old. Even with this restriction, we could potentially still see a bump at 60 (without the grant), as this is the official age of retirement in South Africa. However, we show that life satisfaction increases among non-recipients in the household. Given the consistency of the results across all these different specifications, we rule out retirement as a confounding factor in our analysis.

Other Factors—Other non-monetary factors that determine subjective well-being may be changing around the age of 60 due to the receipt of the grant. While the many mechanisms through which income acts in changing subjective well-being are not a source of concern, things such as abrupt changes in household composition may affect subjective well-being independently of income and confound our results. Indeed, Edmonds, Mammen and Miller (2005) find changes in household composition upon receipt of the grant when focusing on female grant recipients and Ardington, Case and Hosegood (2009) find evidence that the receipt of the Older Person's Grant may increase the number of working age individuals migrating to work, while Abel (2019) shows decreases in labor supply of other household members. While Table 1 shows strong balance at the household and individual levels for the two groups and Figures A.5 and A.6 in the Appendix show no discontinuous changes in key household composition, health, and neighborhood characteristics in our sample across the grant age threshold. Nonetheless, we control for household composition and labor supply at the extensive and intensive margins in our econometric specifications.

Apartheid and Care—Another potential factor that could challenge our identification strategy is a change in life satisfaction due to the grant regardless of income, such as through a sense of feeling cared for by the state or other entity. While this type of concern can apply to any cash transfer program (including randomized ones), it may be more of a concern in this context as the Older Person's Grant is viewed as a post-Apartheid milestone that extended and improved social services for non-white South Africans (Case and Deaton, 1998).

4 Results

4.1 Overall OLS

Table 3 shows results of ordinary least squares regressions with individual reported life satisfaction on a 10 point scale as the dependent variable. These results are for the entire pooled sample. Consistent with prior research, we find that well-being has an approximate U-shape with respect to age (Blanchflower and Oswald, 2008; Wunder et al., 2013) and that life satisfaction is positively related to being female (Blanchflower and Oswald, 2004; Graham and Chattopadhyay, 2013), married (Diener et al., 2000; Mookherjee, 1997), and more highly educated (Ross and Van Willigen, 1997; Michalos, 2008). Perceiving oneself to be in ill health (Palmore and Luikart, 1972) and having heart problems (Aström, Asplund and Aström, 1992) are both negatively related to life satisfaction. Column 1 shows the estimated coefficient on the log of household income per capita without any controls except for wave fixed effects since we are using panel data. This coefficient suggests a strong correlation between household income per capita and subjective well-being consistent with the pattern observed in Figure 2. A 20% increase in income is associated with a 0.112 overall increase in life satisfaction. The magnitude of this effect is large and roughly equivalent to the differential for those with and without heart problems .

The results in column 2 add a number of individual and household characteristics that potentially influence subjective well-being and are associated with household income. The estimated coefficient on income decreases yet remains statistically significant. Adding neighborhood-level controls and district-wave fixed effects, as we do in column 3, does not change the estimated OLS coefficient in a statistically significant way.

Finally, in column 4, we run a fixed effect regression and find that the estimated coefficient on the log of household income per capita is reduced significantly to 0.255. This is consistent with other work that suggests that not taking into account certain personality traits can bias the income to subjective well-being estimates (Powdthavee, 2010; Ferrer-i Carbonell and Frijters, 2004). More importantly, this decrease in the estimated coefficient is consistent with increased attenuation bias due to fixed effects estimates where the signal-to-noise ratio decreases when income is differenced out (Freeman, 1984; Bound and

TABLE 3: OLS and Individual Fixed Effects Results

Dep Var: Life Satisfaction (1-10)	(1)	(2)	(3)	(4)
Log(HH Income Per Capita)	0.564***	0.456***	0.421***	0.254***
	(0.0183)	(0.0190)	(0.0182)	(0.0238)
Household: Size		0.0272***	0.0294***	0.0103
		(0.00933)	(0.00804)	(0.0111)
Household: Number of Children		0.0304**	0.0215*	0.0325*
		(0.0139)	(0.0126)	(0.0192)
Household: Number of Elderly		0.310***	0.307***	0.0510
		(0.0279)	(0.0251)	(0.0464)
Married		-0.0432***	-0.0422***	-0.00833
		(0.00260)	(0.00238)	(0.0299)
Age		0.000446***	0.000485***	0.000394***
		(0.0000288)	(0.0000258)	(0.0000988)
Age^2		-0.0369	-0.0385*	-0.0612*
		(0.0242)	(0.0217)	(0.0332)
African		-1.105***	-0.825***	
		(0.0702)	(0.0739)	
Male		-0.0648***	-0.102***	
		(0.0153)	(0.0144)	
Education: Primary		0.116**	0.113***	0.183
		(0.0483)	(0.0393)	(0.113)
Education: Middle		0.214***	0.178***	0.175
		(0.0465)	(0.0357)	(0.116)
Education: Secondary		0.290***	0.247***	0.127
		(0.0520)	(0.0392)	(0.113)
Education: Diploma		0.392***	0.322***	0.128
		(0.0574)	(0.0451)	(0.116)
Education: Tertiary		0.499***	0.477***	0.205
		(0.0773)	(0.0689)	(0.180)
Disability			0.0328	0.0832*
			(0.0349)	(0.0476)
Perceived Ill Health			-0.176***	-0.140***
			(0.0138)	(0.0163)
Heart Problems			-0.130**	-0.194**
			(0.0586)	(0.0812)
Urban			-0.169***	-0.157*
			(0.0552)	(0.0839)
On Electric Grid			0.191***	0.212***
			(0.0485)	(0.0633)
Neighborhood: Rubbish Pickup			0.204***	0.210***
			(0.0473)	(0.0637)
Neighborhood: Street light			0.0566	-0.00639
			(0.0403)	(0.0464)
Constant	4.078***	5.583***	5.882***	4.989***
	(0.0716)	(0.130)	(0.159)	(1.008)
Wave Fixed Effects	✓	✓		
District-Wave Fixed Effects			✓	✓
Individual Fixed Effects				✓
N	94,476	94,476	94,476	94,476
R^2	0.070	0.110	0.186	0.105

Notes: Standard errors clustered at the original (i.e., wave 1) sampling cluster area are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Krueger, 1991; Bound et al., 1994).[21] While we control for potentially important individual fixed effects, we are likely worsening the bias due to measurement error.

We place lower bounds on our OLS results based on the insights of Altonji, Elder and Taber (2005) and the methods of Oster (2019). With this approach, we generate bounds on the size of the effect by first estimating a regression without control variables (Column (1)) and then estimating a regression including a litany of additional control variables (Column (3)). By assuming a maximum R^2 and the relative explanatory power of unobserved vs observed variables,[22] we put bounds on the coefficient of interest—in our case the effect of income per capita on life satisfaction. Assuming that unobservable variables are just as influential as the observable controls we use in Column (3), we estimate a lower bound coefficient of 0.208. Taken differently, this method suggests that unobservable selection needs to be at least 1.45 times as important as selection on observables to nullify the positive effect we are observing.[23] This suggests that the sign of the coefficient and its statistical significance is fairly robust to unobserved omitted variables.

4.2 Restricted Sample and the Older Person's Grant

In this section we exploit the receipt of the Older Person's Grant at age 60 as an exogenous shock to income as outlined in Section 3.2. To begin this analysis we start by answering the question: Does the grant affect the subjective well-being of the recipient? Figure 4(A) displays the life satisfaction for all individuals in our sample between age 40 and 80. The figure clearly shows that average life satisfaction jumps by about 0.25 points (0.11 SD) at age 60, but this jump may not be solely the result of the receipt of the old age grant—some individuals may be changing their labor supply for example. Figure A.4 in the Appendix

[21] If household income per capita is fairly persistent, then a FE regression differences out a lot of the signal and we are left with mostly noise.

[22] This relies on an assumption about the maximum possible R^2 of the specification, R_{Max}. The smallest possible value of R_{Max} is clearly the R^2 from the regression with controls and the largest mathematically possible value is one. In this setting, however, where we use household and individual-level survey data to measure life satisfaction, it is well-known that such variables are usually measured with considerable error (McKenzie, 2012). Therefore, assuming R_{Max} to have a value of one is overly conservative. We use the approach suggested by Oster (2019), which sets R_{Max} equal to 1.3 $\times$ the R^2 from the regression with controls.

[23] Conducting this exercise with the fixed effect regression in Column(4) gives us a lower bound coefficient of 0.192 and the importance of unobservable selection should be 4.95 times the observable selection to nullify results.

shows that there is no matching sudden decrease in labor force participation at age 60.[24] In this Figure, we can see that there seems to be a decline in life satisfaction in later years; this is likely due to circumstances that vary with age—for example chronic illnesses of self and others in the household or lower per capita household income overall due to the aging of other members of the household. Or perhaps this decrease may be due to the glow of initial increase in income fading away over time.

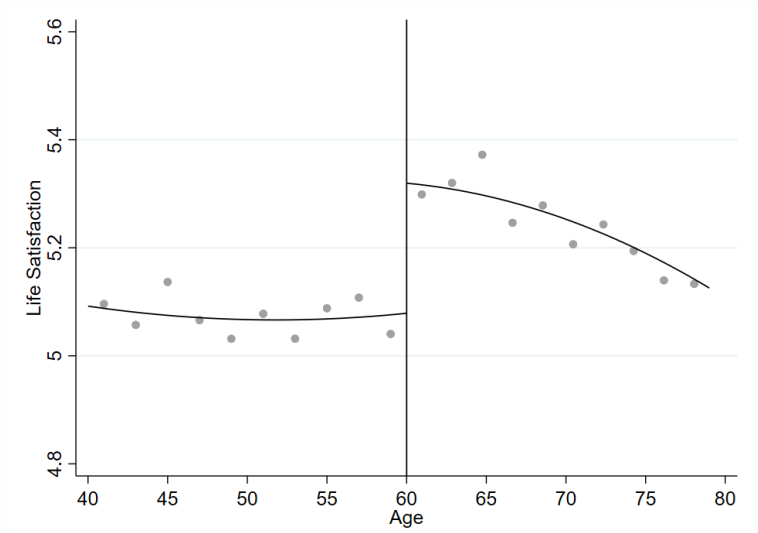
We turn the focus in Figure 4(B) to our specific sample: economically inactive individuals younger than but within five years of age 60 and economically inactive individuals up to five years above the age of 60 who were also out of the labor force when they were below 60. We find a similar, if slightly larger jump in life satisfaction at the age of 60. Moreover, appendix Figure A.7 shows a similar jump when—exploiting the panel nature of the data—we restrict the analysis to the same individuals over time: we start with individuals who are within a few years of turning 60 and out of the labor force both before and after age 60. We then use their observed life satisfaction in later waves after turning 60 to construct the Figure. Applying a fuzzy continuous regression discontinuity approach with grant receipt as our treatment and age as our running variable, in our restricted recipient sample, we estimate a statistically significant effect of grant receipt on life satisfaction of 0.62 with standard error of 0.26.[25] At least at the individual recipient-level, the unconditional cash transfer does seem to increase reported life satisfaction.

In Section 3.2 (Table 2) we show that several household-level measures of economic well-being improve due to the grant. Next we show that this leads to average increases in life satisfaction for all members of the household. We exploit the discontinuity in receipt of grant income shown in Figure 3 and restrict the sample to individuals in households with at least one economically inactive family member close to the age of 60 (as we did for the estimates in Table 2).[26] Table 4 shows these results for different age ranges, with

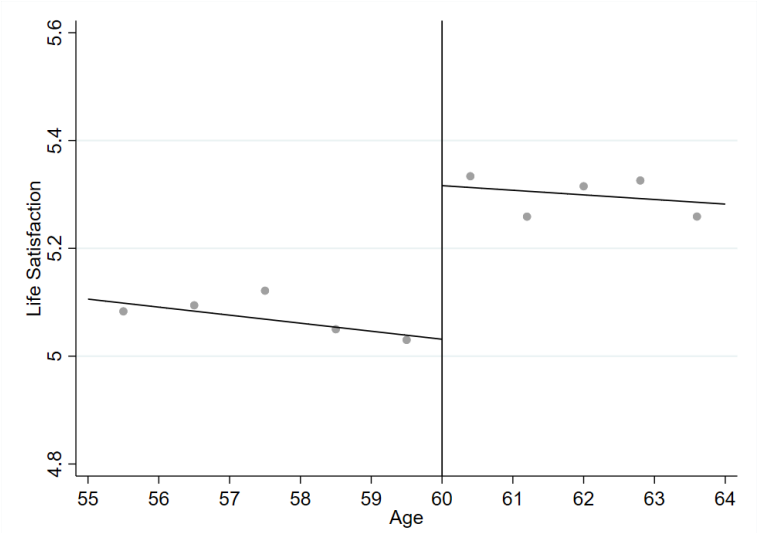
[24] This is not surprising as the grant is not conditional on labor force participation and the majority of individuals have incomes that are well below the means test.

[25] Different approaches to selecting bandwidths lead to slightly different estimates of the effect of grant receipt. We use Eicker-Huber-White heteroskedasticity robust standard errors in our analysis due to its superior coverage when using discrete running variables and small bandwidths where bias from misspecification is less pronounced (Kolesár and Rothe, 2018).

[26] This includes the household members around the age of 60.



(A) Average life satisfaction by age for all.



(B) Life Satisfaction around Grant threshold age for our specific study group of economically inactive individuals.

FIGURE 4: Life satisfaction jumps at age 60. In Figure (A) we show this jump for all individuals around age 60. In Figure (B) we limit the analysis to our restricted sample of individuals above the age of 60 who were also out of the labor before. Figure A.7 in the Appendix shows a similar jump for the same individuals before and after they themselves turn 60 with the condition that they were out of the labor force both before and after .

each successive row showing results for more narrow windows.[27] The first row shows results for individuals in households with members between ages 54 and 65 and the fifth row shows results those with a household member between ages 58 and 61. We show

[27] As discussed in Section 3.2, this instrumental variable approach is akin to fuzzy regression discontinuity, however, our treatment is continuous (household income per capita). We show results for several age ranges that include the optimal bandwidths estimated using fuzzy regression discontinuity methods.

TABLE 4: Restricted Samples OLS and IV Results

		OLS			IV		
		(1)	(2)	(3)	(4)	(5)	(6)
Age Range 54-65 N=18,952	*Log(HH Income Per Cap)*	0.751*** (0.049)	0.537*** (0.053)	0.305*** (0.097)	1.349*** (0.380)	1.158** (0.526)	1.774*** (0.427)
Age Range 55-64 N=16,356	*Log(HH Income Per Cap)*	0.745*** (0.052)	0.557*** (0.056)	0.301*** (0.102)	1.288*** (0.423)	1.114** (0.560)	1.496*** (0.430)
Age Range 56-63 N=13,617	*Log(HH Income Per Cap)*	0.772*** (0.057)	0.570*** (0.062)	0.354*** (0.117)	1.259*** (0.486)	1.062* (0.574)	1.438*** (0.467)
Age Range 57-62 N=10,664	*Log(HH Income Per Cap)*	0.837*** (0.060)	0.606*** (0.067)	0.478*** (0.142)	1.325** (0.599)	1.281* (0.671)	1.320** (0.655)
Age Range 58-61 N=7,290	*Log(HH Income Per Cap)*	0.870*** (0.073)	0.612*** (0.081)	0.318 (0.214)	1.970** (0.842)	2.311** (1.044)	2.629** (1.143)
	Controls		✓	✓		✓	✓
	Individual Fixed Effects			✓			✓

Notes: Standard errors clustered at the original (i.e., wave 1) sampling cluster area are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Controls include all the variables listed in column (3) of Table 3 except wave-district fixed-effects. In these IV regressions, we control for wave and district fixed effects independently.

the estimates using OLS without any controls, with controls (same as those in column 3 of Table 3), and finally controlling for individual fixed effects in columns 1, 2, and 3, respectively. The estimated coefficients for these restricted samples using OLS and fixed effects regressions are very similar to those for the full sample shown earlier in Table 3.

In columns 4, 5 and 6, we show results for instrumental variable regressions without controls, with controls, and fixed effects.[28] The estimated coefficients in Column (5) suggest that a 20% increase in household income per capita increase average life satisfaction by approximately 0.21 points. The fixed effects instrumental variable results exhibit a similar pattern with larger point estimates. Using a continuous fuzzy regression discontinuity approach gives a similar point estimate of 1.496 (standard error of 0.671). These estimated impacts of income on subjective well-being are robust to different log-normal transformations of the life satisfaction variable (Bond and Lang, 2019).[29] The average increase in life

[28] As expected given the results in Table 2, these IV regressions have strong first stage results (shown in Appendix Table A.2).

[29] As Bond and Lang (2019) point out, if the variances among the two groups are not equal, findings could be reversed with different transformations (concave vs convex) of the numbers associated with different levels of

satisfaction among the grant recipients was about 0.25 points, slightly higher than what would be predicted by the average increase in household income that is estimated to be around 20% in this sample. This suggests that the recipient may initially experience a bigger increase in subjective well-being than the average member of the household. While this makes sense intuitively—the recipient potentially has more ownership of this extra income—it raises the question: is the estimated average effect solely driven by the recipients?

Our sample contains the individuals who are around the eligibility threshold—the recipient and the potential recipient of the transfer—as well as other members of the household. To what degree is this estimated average effect driven by the individuals actually receiving the transfers? Does the subjective well-being of other adult household members also increase due to the influx of added income to the economically inactive grant recipient? We now focus on individuals who are not grant recipients, but still live with an economically inactive adult household member in the eligible age range. The results in Table 5 show these estimates. The estimated coefficients are quite similar in magnitude to those in Table 4, suggesting that the added household income is also affecting the well-being of other household members on average and the size of the effects are comparable, though slightly lower.

Heterogeneity—In Appendix Table A.3 we show that the effects on other members of the household depends on the sex of the recipient. Several studies have shown—including in South Africa—that the identity of the recipient of the added income affects the intra-household distribution of this income and on what it is used for (Duflo, 2003; Schady and Rosero, 2008; Phipps and Burton, 1998). The results in Table A.3 suggest that non-recipient household members are more likely to benefit when the recipient of the transfer is female, a finding that supports prior research. However, as 75% of the recipients in our restricted study sample are female, the lack of statistical significance when recipients are male may be due to low levels of statistical power. The point estimates are similar in the two groups. We do not find statistically different point estimates by sex or by household

life satisfaction. The variances among the two groups in our restricted samples are not statistically different, however, we estimated the regressions in Table 4 with different transformations and the pattern of results remains the same with both convex and concave log-normal transformations. The results are similarly robust to the *dichotomous-around-the-mean* robustness test suggested by Bloem and Oswald (forthcoming).

TABLE 5: Restricted Samples OLS and IV Results: Non-recipient

		OLS			IV		
		(1)	(2)	(3)	(4)	(5)	(6)
Age Range 54-65 N=11,791	*Log(HH Income Per Cap)*	0.763*** (0.056)	0.580*** (0.060)	0.365*** (0.084)	0.554** (0.275)	0.570* (0.314)	1.197** (0.506)
Age Range 55-64 N=10,126	*Log(HH Income Per Cap)*	0.759*** (0.059)	0.598*** (0.064)	0.341*** (0.093)	0.482 (0.294)	0.616* (0.333)	1.039** (0.527)
Age Range 56-63 N=8,395	*Log(HH Income Per Cap)*	0.788*** (0.066)	0.611*** (0.071)	0.424*** (0.109)	0.632* (0.336)	0.669* (0.372)	0.834 (0.550)
Age Range 57-62 N=6,524	*Log(HH Income Per Cap)*	0.873*** (0.070)	0.658*** (0.079)	0.560*** (0.136)	1.067** (0.419)	1.005** (0.412)	0.426 (0.807)
Age Range 58-61 N=4,426	*Log(HH Income Per Cap)*	0.905*** (0.086)	0.646*** (0.093)	0.410** (0.205)	1.301** (0.636)	1.380** (0.606)	1.216 (1.371)
	Controls		✓	✓		✓	✓
	Individual Fixed Effects			✓			✓

Notes: Standard errors clustered at the original (i.e., wave 1) sampling cluster area are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Controls include all the variables listed in column (3) of Table 3 except wave-district fixed-effects. In these IV regressions, we control for wave and district fixed effects independently. These results are for members of the household that are not near the grant eligibility threshold.

wealth, though because our specification has household income per capita in log form, the grant itself likely has a larger relative effect on the poor as it is a much larger percent of their total household income.

Generalizability—Most of the elderly in South Africa benefit from the Older Person's Grant and nearly 35% of households in our sample have a member who is above the age of 60. However, do our results translate to the rest of the population? The OLS results among our sample are similar to those estimated for the entire sample which is encouraging. Panel datasets such as this one also allow for the application of panel data methods popularized by Arellano and Bond (1991).[30] Dynamic panel data methods come with their

[30]Panel data allow us to use dynamic panel data methods. Assuming sequential exogeneity and that the error terms are serially uncorrelated, these methods use the lagged levels of income as instruments for income in a first-differenced equation (Anderson and Hsiao, 1982; Arellano and Bond, 1991; Holtz-Eakin, Newey and Rosen, 1988). The intuition behind this estimation strategy is that after controlling for individual fixed effects, lagged income, psychological well-being, and other time varying individual characteristics, what remains in the error terms is random. This way the lagged levels are correlated with the first differences—thus relevant,

own set of assumptions on sequential exogeneity and serial correlation in the error terms for the estimators to be consistent. These assumptions, however, are different from those required for our main methods above. Different dynamic panel specifications yield statistically significant coefficient estimates between 0.65 and 1.86. These are larger than the OLS estimate and are similar in magnitude to our main estimated effects shown in Tables 4 and 5.

The instrumental variable results suggest that the causal impact of a change in income on life satisfaction is larger than that estimated using OLS. This suggests that correlational measures of the effect of income on subjective well-being may be underestimating the effect of income. This is similar to the conclusion of Powdthavee (2010), who explains that this finding may be indicative of the importance of accounting for measurement error in the income variable as well as the exclusion of some variables such as work hours and comparison income, which are known to be positively related to income but negatively related to life satisfaction.

5 Conclusion

This paper explores the causal impact of income on subjective well-being using recent panel data from South Africa. When we restrict the sample to individuals who are part of households with a member near the eligibility age of 60 and use eligibility for the South Africa Older Person's Grant as an instrument for household income per capita, we find that increases in income lead to a large and significant improvement in subjective well-being. Specifically, we find that a 20 percent increase in household income increases life satisfaction by 0.2 points on a 10-point scale, which is roughly on the same scale as the decrease in life satisfaction after a person develops heart problems. This effect is large and statistically significant, and is about twice the size of reduced form OLS estimates, reinforcing the conclusion of recent studies that correlational estimates may be underestimating the effect of income on subjective well-being (Powdthavee, 2010).

and are uncorrelated with the remaining error terms—and thus valid instrumental variables. Arellano and Bover (1995); Blundell and Bond (1998) extend the method by making an additional assumption that the first differences are uncorrelated with the fixed effects allowing for more instruments and improved efficiency.

We address several concerns that could lead to a violation of the assumptions we require for our identification strategy including retirement and other changes that could take place when an individual turns 60 and starts receiving their grant. However, we restrict our sample in such as a way as to minimize these concerns and show that the effect extends to other members of the household.

The paper contributes to the literature on the economics of subjective well-being by providing a plausible estimate of the causal effect of household income on the life satisfaction of individuals for a broadly representative sample in a developing country. We show that a large unconditional cash transfer program in a country with high levels of poverty such as the South Africa Older Person's Grant program increases several household-level measures of economic well-being including household income per capita, which increases by nearly 20% and significantly improves the subjective well-being of both recipients and their family members. As more research is done in this area, we will continue to increase our understanding of the complex relationship between economic well-being and subjective well-being.

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Appendix

Tables

TABLE A.1: Life Satisfaction for different groups over time

	Mean 2010	Mean 2017
Overall	4.96	5.46
Sex		
Female	5.34	5.64
Male	4.11	5.04
Race		
Black	4.48	5.31
Other	6.88	6.17
Marital Status		
Married	5.58	5.78
Not Married	4.71	5.38
Poverty Status		
Poor	4.11	5.04
Not Poor	5.34	5.64
Location		
Urban	5.34	5.60
Traditional or Rural	4.41	5.25
Age		
20 and below	4.81	5.54
21-30	4.83	5.38
31-40	5.03	5.40
41-50	4.85	5.52
51-60	5.30	5.47
61-70	5.40	5.57
71-80	5.05	5.81
81 and above	4.74	4.94

Notes: We show average reported life satisfaction (on 10-point scale) for different groups in two different waves of NIDS.

TABLE A.2: First Stage regression results

		IV First Stage	Effective F-Stat
Age Range 54-65 N=18,952	*Number of HH members 60-65*	0.099*** (0.014)	**49.51**
Age Range 55-64 N=16,356	*Number of HH members 60-64*	0.103*** (0.015)	**46.81**
Age Range 56-63 N=13,617	*Number of HH members 60-63*	0.105*** (0.017)	**37.23**
Age Range 57-62 N=10,664	*Number of HH members 60-62*	0.108*** (0.021)	**26.82**
Age Range 58-61 N=7,290	*Number of HH members 60-61*	0.094*** (0.024)	**15.26**

Notes: Standard errors clustered at the original (i.e., wave 1) sampling cluster area are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1. First stages of the IV regressions show very strong predictive value of the instrumental variable for the log of household income. These first stage results correspond to the IV regression results in Table 4 column (5). Effective F-statistics according to Olea and Pflueger (2013) are shown. First stage results for the Fixed Effects IV have larger coefficients and F-statistics for the excluded instrument than those presented here.

TABLE A.3: Heterogeneity by Recipient Sex

		Female	Male
		(1)	(2)
Age Range 54-65	*Log(HH Income Per Cap)*	0.479*	0.987
		(0.251)	(0.641)
Age Range 55-64	*Log(HH Income Per Cap)*	0.677***	0.847
		(0.287)	(0.577)
Age Range 56-63	*Log(HH Income Per Cap)*	0.738**	0.542
		(0.316)	(0.541)
Age Range 57-62	*Log(HH Income Per Cap)*	0.838**	1.019*
		(0.370)	(0.568)
Age Range 58-61	*Log(HH Income Per Cap)*	1.364**	0.856
		(0.611)	(0.571)

Notes: Standard errors clustered at the original (i.e., wave 1) sampling cluster area are presented in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$. These results are calculated using similar specifications to those in 5; the effect on other household members (non-recipients) differentiated by the sex of the recipient. The results suggest that there is more intra-household redistribution of income if the grant recipient is female.

Figures

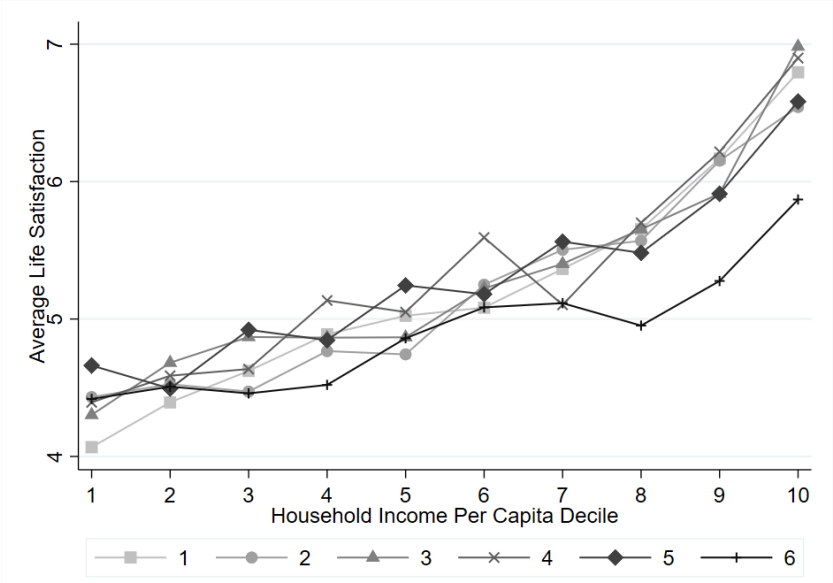

FIGURE A.1: Income per capita decile is calculated within each household size and wave. Difference in average life satisfaction here is even more pronounced.

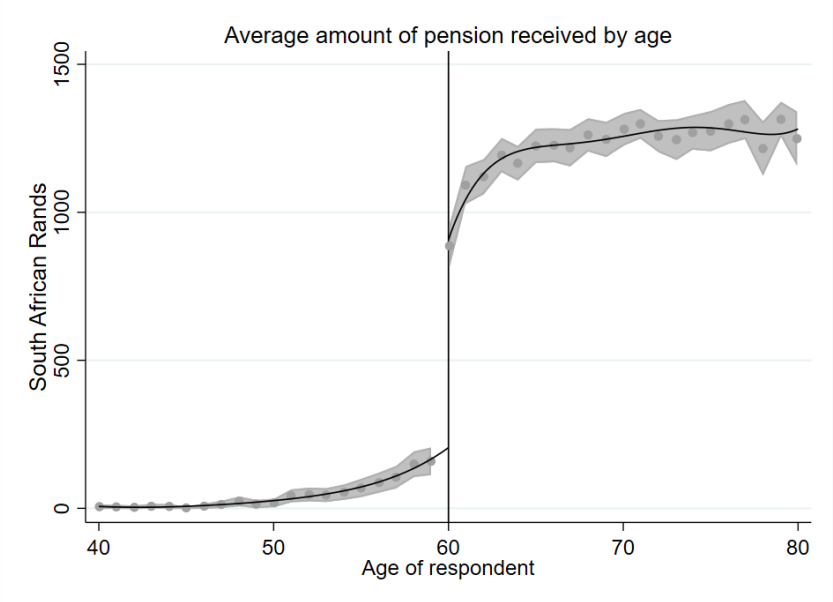

FIGURE A.2: Individual-level average amount of old age grant received by age. There is a clear discontinuity of grant receipt around the age of eligibility of 60.

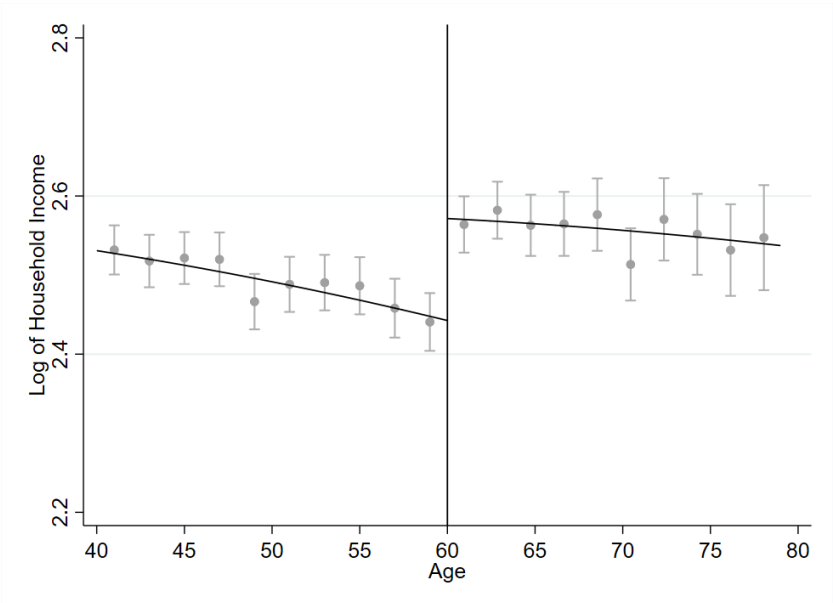

FIGURE A.3: The log of household income per capita for individuals around the threshold age of 60. Without sample restrictions or controls, we can see that household income jumps when a member has reached age 60.

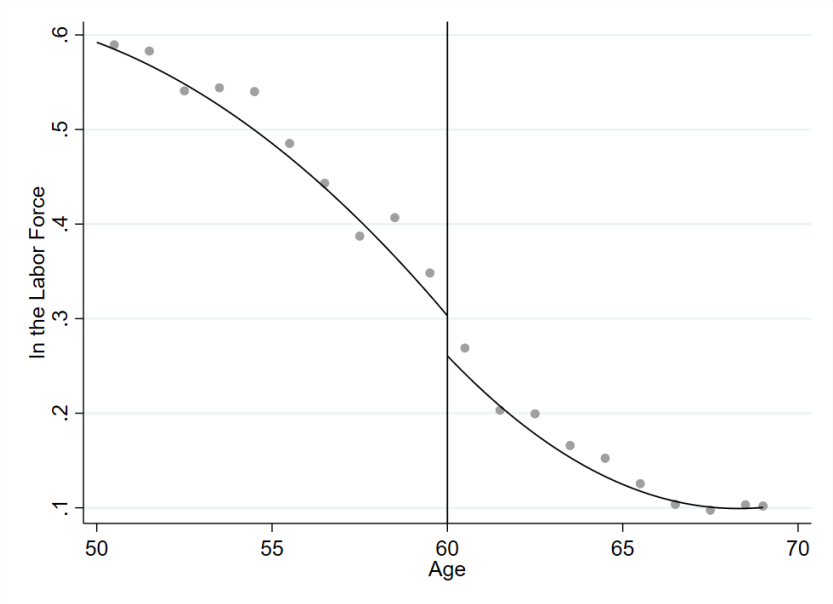

FIGURE A.4: Individual-level labor force participation by age. Labor force participation is clearly decreasing by age but there is no clear discontinuity at age 60 as you often see in other countries where pensions kick in at retirement. The Old-Age Grant in South Africa is means tested, but the overwhelming majority earn incomes well below the threshold.

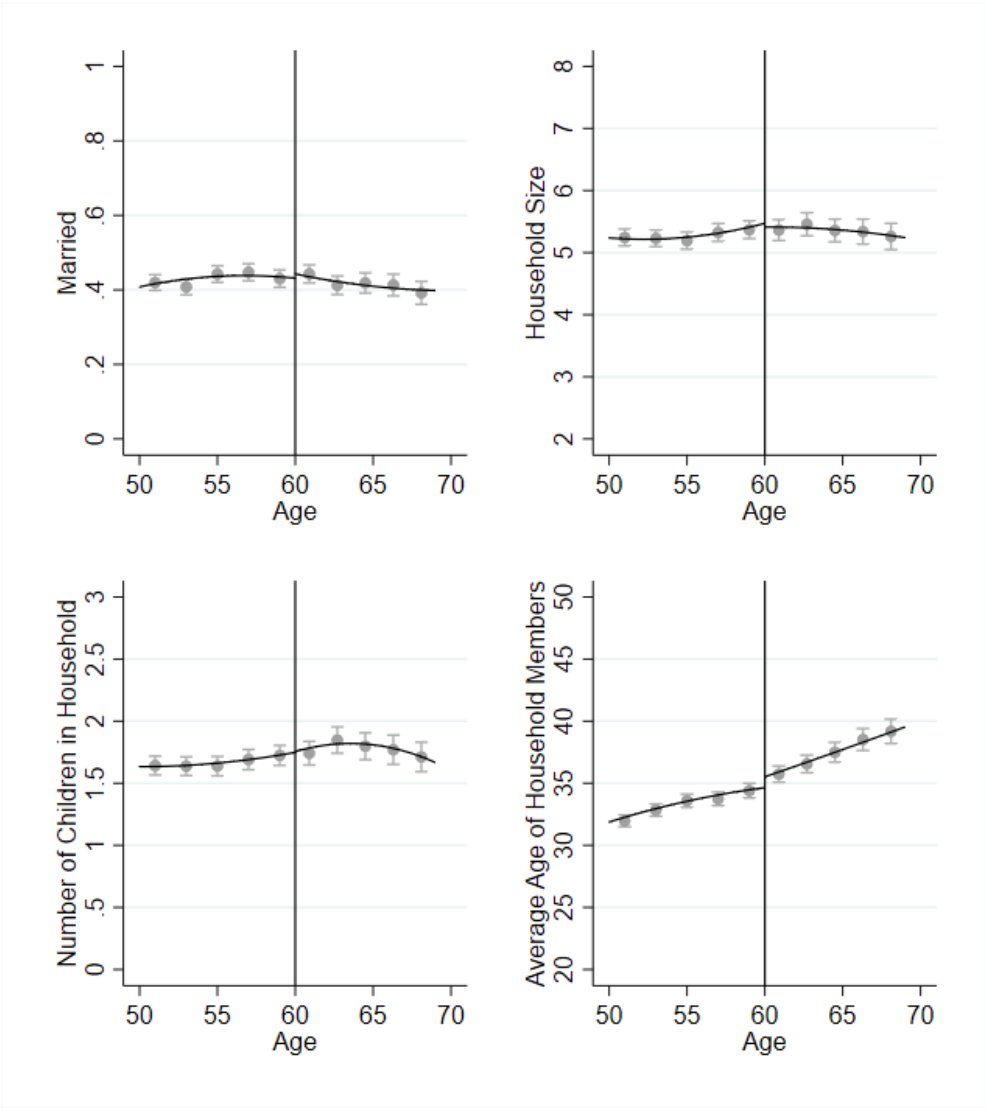

FIGURE A.5: Share of individuals who are married, household size, and number of children in the household, and average household size do not change significantly around the grant eligibility threshold.

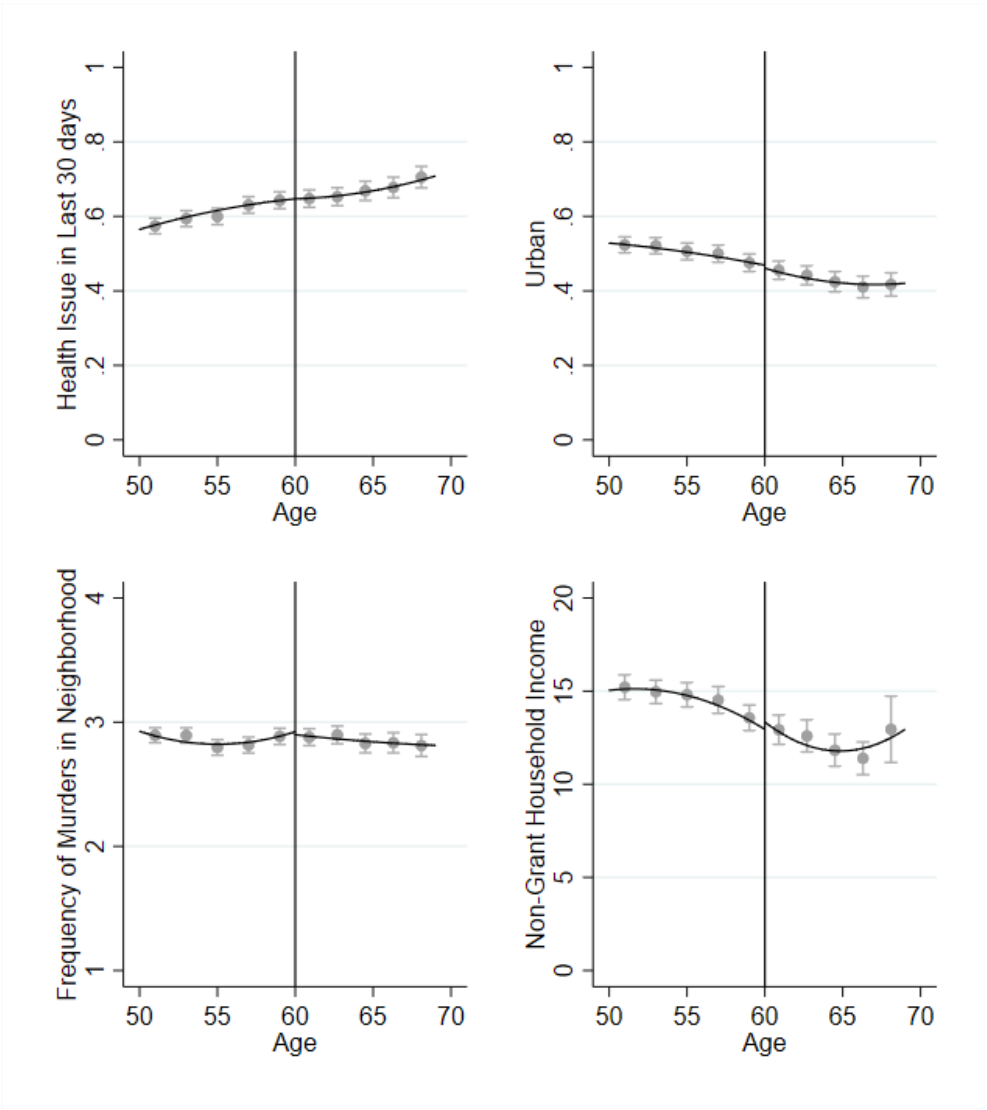

FIGURE A.6: Share reporting health issue in the last 30 days, the share living in an urban area, reported frequency of neighborhood violence, and non-grant household income per capita do not change discontinuously around the grant eligibility threshold.

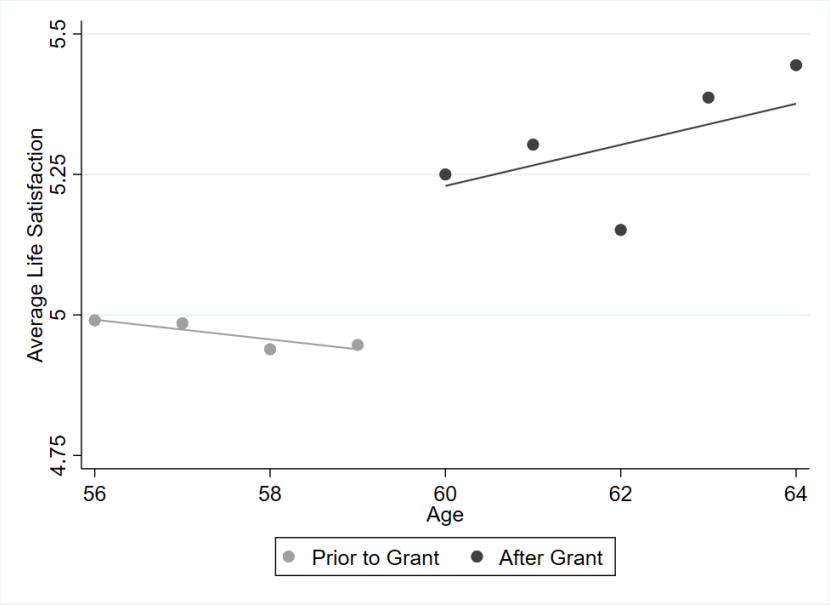

FIGURE A.7: Using the panel and restricting our analysis to the same individuals before and after age 60, we still see a similar bump in life satisfaction. As opposed to Figure 4 which contains any economically inactive individuals before and after age 60, the sample used to form this figure is different. We use a sample of people who we observe before turning 60 and then, exploiting our panel, we show the life satisfaction level for the same group after turning 60.